

**The Use of Remote Sensing to Map and Monitor Coastal Dune Vegetation Change
at Southampton, Ontario, Canada**

by

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Abstract

Coastal dune ecosystems in the Great Lakes Basin are fragile, rare ecosystems that are under increasing threat due to anthropogenic and natural forces. The Chantry Dune system in Southampton, Ontario is one of five major dune systems along the eastern shores of Lake Huron. The dune complex provides habitat for a diverse range of vegetation species, some of which are endemic, rare, and threatened. This research mapped and monitored dune vegetation change at the Chantry Dune system from 2005-2012 using multi-temporal normalized difference vegetation index (NDVI) images produced from QuickBird and GeoEye-1 imagery acquired in 2005 and 2012, respectively. Next, a post-classification comparison change-detection technique was applied to determine the patterns of change in vegetation cover. Finally, the maximum-likelihood classifier (MLC) was applied to the GeoEye-1 data to produce a land-use/land-cover map. Results revealed that increased vegetation growth occurred throughout the dune system while NDVI values remained unchanged or increased slightly from 2005-2012. Application of the MLC resulted in a map output with an overall classification accuracy of 97%. The results and outcomes of this research will provide much needed baseline information, which can be used by local stakeholders and authorities to improve dune management practices.

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*Brodie Hague
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Dedication

*In loving memory of my grandfather: **ROBERT NEAL FISHER (1935 - 2012)**. The cottage in Southampton will never be the same without you.*

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Chapter One: Introduction

1.1 - Background

Of the diverse range of ecosystems in the Great Lakes Basin, coastal dune ecosystems are considered among the most fragile and rare (SOLEC, 2009). These aeolian ecosystems provide several important functions that influence both natural and human systems. Coastal dune systems provide habitat to numerous species of flora and fauna, some of which are globally rare, provincially endangered, or endemic to the Great Lakes region (Clark and Peach, 2010; Gauthier et al., 2010; Jalava et al., 2003). In addition, coastal dunes provide valuable shoreline protection from high water levels and storm events and have been viewed by coastal geographers as “nature’s shore protection” (Peach, 2003, pg. 2). The tranquility and ecological diversity of coastal dune systems also provide economic benefits to local communities through tourism and recreation opportunities on the adjacent beaches (Peach, 2006; van Dijk and Vink, 2005). Given the important role of coastal dunes, it is imperative that these complex and dynamic systems are managed in an effective and sustainable manner.

Coastal dune systems are dynamic and subject to a variety of natural processes. Wave action is continually eroding and depositing sand onto the shore (**Figure 1.1**). During storm events and high lake levels, waves erode the beach and carry the sand offshore resulting in the formation of a sandbar. The offshore sandbar absorbs and reduces wave energy before the waves reach the shore. In contrast, calm wave action and low lake levels will transport the sand from the sandbar back onshore where it will be deposited on the beach (Peach, 2007). Sand is then transported by the wind via three methods, including suspension, saltation, and surface creep. Suspension involves the movement of sediment aloft in the airstream while saltation transports sediment through a series of “bounces” or “hops” across the surface. Surface creep involves the

rolling of larger particles across the surface due to the wind or the impact of particles being moved by saltation (Christopherson and Byrne, 2006). A majority of sand particles are moved via saltation; however, surface creep may account for approximately 20-25% of sand particle movement (Christopherson and Byrne, 2006; Ahnert, 1998; Bagnold, 1954).



Figure 1.1: A self-sustaining dune ecosystem. (Source: Peach, 2007).

The quantity of the sand moved by the wind is influenced by a variety of factors including wind strength, wind duration, the size of the sand particles, and water levels (Peach, 2007). In periods of high water levels, less beach area is exposed to wind erosion, while during periods of low water levels, a larger area of the beach is exposed. Thus, periods of low water tend to result in dune formation, while periods of high water levels result in natural dune erosion (Lake Huron Centre for Coastal Conservation, 2015; Wilcox et al., 2007; Peach, 2003).

The formation of dunes requires a sufficient supply of sand and wind velocity for sediment transportation. Sand deposition occurs when the wind encounters an obstacle, such as vegetation, which in turn reduces wind velocity and the capacity for the wind to carry sediment. Over time, the continued accumulation of sand results in the formation of a dune, which as it continues to grow in both height and extent, prevents sand from being blown inland and protects

the shoreline during storm events (Peach, 2007; 2006). As previously mentioned, it is not surprising that coastal dunes are often referred to as “nature’s shore protection.” If the protection provided by dune systems had to be replaced with a human-built structure, such as a revetment, the cost would be millions of dollars (Peach, 2003).

As dune systems are highly susceptible to erosion, especially those composed of finer sand, dune vegetation is an important feature of these coastal landforms as it promotes the trapping and deposition of sand. Dune vegetation and their associated underground root structure provide stability and further prevent the erosion of sand, especially during periods of enhanced erosion (Cochard et al., 2008; Peach, 2007). American Beach Grass (*Ammophila breviligulata*), is particularly effective in trapping sand and is one of the most popular dune vegetation species in the dunes along Lake Huron. Given this effectiveness, American Beach Grass is a common plant used in dune restoration and management efforts across the Great Lakes Basin (Emery and Rudgers, 2011; Peach, 2007). As the height of the dune increases through the trapping of sand, dune vegetation growth will, in turn, accelerate in response to these changes (Broome et al., 1982). The loss or absence of dune vegetation can result in increased erosion, blowouts, and the recession of the shoreline, which can have numerous implications for shoreline management (Peach, 2003; Lawrence, 1997; Sherman and Bauer, 1993). The presence of dune vegetation therefore “represents the difference between a mobile pile of sand and a stabilized dune” (Salmon et al., 1982 as cited by Peach, 2006, pg. 16). Accordingly, the overall health of the dune system and dune vegetation health are inextricably interlinked.

Although dune vegetation can be impacted through natural processes, human activities can also pose considerable stress to dune vegetation and these impacts have been well documented in the literature (Davenport and Davenport, 2006; Bonanno et al., 1998; Andersen,

1995; Bowles and Maun, 1982). Great Lakes coastal dune ecosystems, especially those along the Lake Huron shore, are under considerable stress as a result of shoreline development and human disturbance (Environment Canada and the U. S. Environmental Protection Agency, 2014; Peach 2006; Bowles and Maun, 1982). Furthermore, coastal dune ecosystems are also under threat from invasive plant species that spread uncontrollably, thereby impacting native plant species and the overall ecology of the dune system (Clark and Peach, 2010; Gauthier et al., 2010; D'Ulisse and Maun, 1996). Despite increased pressures on dune systems, few studies have examined human impacts on coastal dunes in the context of the Great Lakes Basin (van Dijk and Vink, 2005; Bowles and Maun, 1982). In order for these valuable resources to be managed in a sustainable manner, coastal managers, municipalities, and local stakeholders must possess knowledge including spatial inventories of the dune system to inform decision-making and develop efficient management plans (Lake Huron Centre for Coastal Conservation, 2012; Peach, 2003; Lawrence, 1997).

The ecological sensitivity of coastal dune systems presents several challenges and limitations for researchers investigating the various processes occurring within these environs. Although it is imperative that these ecosystems are monitored to inform management and stewardship decisions, such initiatives must be completed in a non-invasive and careful manner to avoid damage. Accordingly, geospatial technologies including remote sensing provide unique opportunities to study these ecosystems while simultaneously preserving their ecological integrity. Remote sensing can be defined as the collection of information regarding the electromagnetic energy reflected off an object by a device that is not in contact with the object being observed (Shellito, 2014). Earth-surface features such as vegetation, soil, built-up areas, and water respond differently to electromagnetic energy. It is from these distinct spectral

characteristics and responses that analysts can extract thematic information to produce useful information products to solve real-world problems.

In the remote sensing of vegetation, near-infrared radiation (NIR) and visible red energy are primarily of interest given that due to the plant's internal structure, healthy photosynthesizing vegetation strongly reflects NIR and absorbs visible red energy. Conversely, unhealthy vegetation and sand reflect less NIR and reflect more visible red energy. A number of vegetation indices have been developed based on this inverse relationship to quantify vegetation properties and provide useful information regarding vegetation health and vigour (Campbell, 2007; Bannari et al., 1995). A notable benefit in using remote sensing to study and monitor vegetation is that remote sensors are often able to detect declining vegetation health and condition before our eyes can detect such change. This valuable information can then be subsequently employed to inform and influence dune management efforts.

Given the important role of vegetation to the integrity and sustainability of coastal dune ecosystems, monitoring vegetation is an important endeavour. However, there is limited research on the use of remote sensing to map and monitor coastal dune vegetation in the Great Lakes Basin, especially along the shores of Lake Huron. With respect to the Chantry Dune system, there is a lack of baseline data and the need to monitor the health and welfare of the dune system has been identified as a prominent management goal by the local government (Town of Saugeen Shores, 2013). It is within this context that the research goal and objectives outlined below were developed. Accordingly, this research project inventories the health of an important dune system using innovative remote-sensing approaches that are readily transferable to other coastal landscapes in the Great Lakes Basin.

1.2 - Research Goal and Objectives

The purpose of this research project was to monitor dune vegetation change at the Chantry Dune system, a coastal dune system along the shores of Lake Huron. The research question for this study was: *What are the patterns of change in vegetation cover within the Chantry Dune system located in Southampton, Ontario, Canada from 2005 to 2012?* The overall goal of this research project was to provide information to local governments, citizens, and stakeholders regarding changes in vegetation cover within the Chantry Dune system to better inform management decisions. To achieve this goal, the following three objectives were identified: first, to produce multi-temporal normalized difference vegetation index (NDVI) images for the Chantry Dune system (2005 to 2012); second, to determine the patterns of change in vegetation cover in the Chantry Dunes from 2005 to 2012 using the post-classification comparison change-detection technique applied to remote-sensing imagery; and third, to produce an accurate land-use/land-cover (LULC) map of the Chantry Dune system using a supervised classification technique. The findings of this research project will provide much needed baseline data to inform local stakeholders and contribute to the development and refinement of current dune management approaches.

1.3 - Study Area

The study area for this research project is the Chantry Dune system (44°29'21.42" N, 81°23'11.22" W) located in Southampton, Ontario, Canada (**Figure 1.2**), one of five major sand dune systems along the eastern shores of Lake Huron (Peach, 2006). Southampton is approximately 230 kilometres northwest of Toronto, Ontario and is one of three communities that comprise the Town of Saugeen Shores. The community of Southampton is situated at the mouth of the Saugeen River where it empties into Lake Huron. The town (population 3,440) is a

popular summer tourist destination due to its beaches, outdoor recreation opportunities, and beautiful sunsets (Saugeen Shores Chamber of Commerce, 2014; Statistics Canada, 2012). The local climate, like many Ontario communities, is strongly influenced by the Great Lakes and can be described as mid-latitude humid continental. The mean annual precipitation is 828.4 mm. The warmest month (July) has a mean daily temperature of 18.7 °C while the coldest month (February) has a mean daily temperature of -6.6 °C (Environment Canada, 2015a).



Figure 1.2: The location of Southamptton, Ontario and the major dune systems on Lake Huron.

1.3.1 - Background and Overview of the Chantry Dunes

The Chantry Dune system is approximately 1 km in length (between Beach and Bay Streets in Southampton) and approximately 8 ha in area (**Figure 1.3** and **Figure 1.4**). The five major dune systems on the eastern shores of Lake Huron include the Chantry Dunes, Point Clark, Sauble Beach, Inverhuron, and Pinery/Ipperwash (**Figure 1.2**). Of these dune systems, the Chantry Dunes, Point Clark, and Sauble Beach are not located within a provincial park which further complicates dune stewardship and management approaches. This is due to the various legislation and regulations that govern the management of dune systems within and outside provincial parks, including the *Provincial Parks and Conservation Reserves Act* and the Provincial Policy Statement (Environmental Commissioner of Ontario, 2013; Ontario Ministry of Natural Resources, 2011; Clark and Peach, 2010; Peach, 2006).

The dune system provides habitat for a diverse range of dune vegetation including American Beach Grass (*Ammophila brevigulata*), Sand Cherry (*Prunus pumila*), Pitcher's thistle (*Cirsium pitcheri*), and Great Lakes Wheat Grass (*Agropyron psammophilum*). Both Pitcher's thistle and Great Lakes Wheat Grass are endemic species in the Great Lakes; Pitcher's thistle is threatened both provincially and nationally while Great Lakes Wheat Grass is globally rare (Gauthier et al., 2010; Peach, 2003). Approximately 1 km offshore from Southampton is Chantry Island (**Figure 1.5**), a Federal Migratory Bird Sanctuary and home to migratory and nesting birds, including the Great Blue Heron, Herring Gull, Piping Plover, and Northern Pintail (Marine Heritage Society, 2012). Accordingly, the Chantry Dunes also provide habitats for animal species, including migratory birds en route to Chantry Island and other habitat locations.

The Chantry Dune system owes its origin to the recession of post-glacial Lake Nipissing, which began approximately 6,000 years ago. The dune system is highly susceptible to erosion

given that it primarily consists of fine sands (Peach, 2003). Furthermore, the composition of the dune complex is significant as it consists of relict deposits—sand that was deposited by geological processes that are not currently occurring. Reinders (1986) concluded that sediment is not being actively contributed to the system from both the north and south of the Chantry Dunes. Therefore, the enhanced erosion of sand and sediment resulting from human activity is detrimental and a permanent loss to the dune system (Peach, 2006).

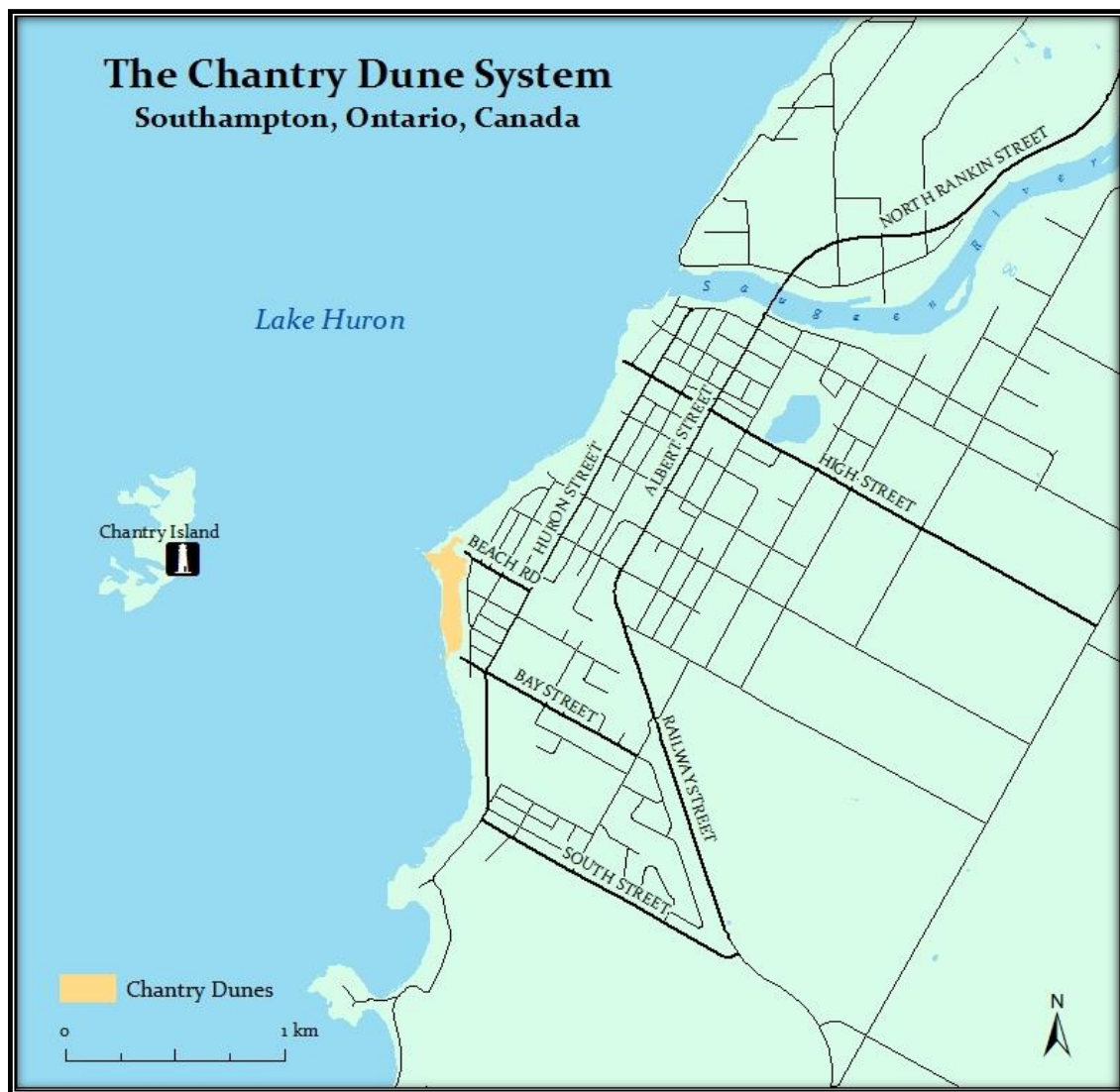


Figure 1.3: The Chantry Dune System's location in Southampton, Ontario.



Figure 1.4: An aerial view of the Chantry Dunes, Southampton, Ontario. (Source: Lake Huron Centre for Coastal Conservation, 2012).



Figure 1.5: Chantry Island, as seen from the dune system, is a Federal Bird Sanctuary and provides a backdrop to the Chantry Dunes. (Source: V. Hague, 2015).

1.3.2 - Chantry Dune System: Conservation and Management

Overall, dune conservation and management on Lake Huron is still in its infancy having only occurred at the municipal level within the last decade (Peach, 2006; van Dijk and Vink, 2005). Shoreline management and dune conservation have gained increased prominence and attention during the late 1980s due to high water levels on the Great Lakes, which resulted in shoreline damage caused by erosion and flooding (Lawrence, 1995). In the early 1990s, the Chantry Dune system was adversely impacted by human activities. In response, the Southampton Beach Association undertook a project, known as the Chantry Dunes Project, to restore the dune system in collaboration with a variety of community organizations. The conservation efforts included the restoration of degraded areas, controlled access to certain areas through the installation of wooden posts and fencing (**Figure 1.6**); and, perhaps most importantly, the education of the local population about the ecological and economic importance of the dune system. Notably, the community was actively engaged and involved in this initiative, one of the first of its kind in Ontario (Peach 2006, 2003).

However, the lack of management guidelines following the completion of the Chantry Dunes Project, in conjunction with the amalgamation of Southampton into the Town of Saugeen Shores in the late 1990s, complicated dune management efforts (Peach, 2006). The development of a management manual for the Chantry Dunes written by the Lake Huron Centre for Coastal Conservation (Peach, 2003) provided the Town of Saugeen Shores with additional guidelines for dune management and conservation approaches. Overall, the dune restoration project was successful in restoring degraded areas of the dune system, restricting pedestrian and vehicular access to certain areas, and increasing citizen awareness of the important role of coastal dunes. The Town of Saugeen Shores has been hailed a dune conservation leader within Ontario in their

attempt to balance the complex and inter-related economic, social, and environmental functions of a waterfront (Peach, 2003).



Figure 1.6: The Chantry Dunes Project (1995) included the installation of wooden posts and fencing to control access through the dune system. (**Source:** V. Hague, 2015).

The town's Waterfront Master Plan, released in 2013 (Town of Saugeen Shores, 2013), outlines the approach taken by the municipality in the development of a sustainable and desirable waterfront. In the development of the Waterfront Master Plan, the Town of Saugeen Shores consulted local residents through open houses and surveys. In particular, notable topics of discussion included the invasion of some dunes onto private property, and the overgrowth of beach grass onto public sidewalks and pathways. Moreover, concerns were raised that some residents were mowing the dune grass to improve their aesthetic views of Lake Huron. Major recommendations included continued public education on the importance of dune ecosystems and the development of a comprehensive by-law that addresses issues related to dune grooming

and the “tampering” of dune vegetation by the public (Town of Saugeen Shores, 2013, pg. 60).

Another notable recommendation relevant to this current research project was the need for continued monitoring of the dune vegetation through the publication of annual reports along with “supporting photographic and other empirical data” (Town of Saugeen Shores, 2013, pg. 62).

1.4 - Sustainability Science and the Remote Sensing of Coastal Dunes

Sustainability science may be defined as “an emerging field of research dealing with the interactions between natural and social systems and how those interactions affect the challenge of sustainability: meeting the needs of present and future generations while substantially reducing poverty and conserving the planet’s life support systems” (Kates, 2011, pg. 19449).

Sustainability science is integrative, transdisciplinary, and seeks to incorporate multiple knowledge, including from non-academics, into discussions and research processes (Lang et al., 2012; Jerneck, 2011).

The use of remote-sensing technologies to map and monitor coastal dune vegetation can be related to sustainability science. In the context of dune management, Peach (2006) discussed how the inclusion of the Southampton community contributed to development and successful execution of the Chantry Dune project in the 1990s. The exchange of knowledge between coastal managers and local citizens about the Chantry Dune system was a bi-directional process that resulted in the co-production of knowledge and the incorporation of this knowledge into management and stewardship strategies. This relates to a prominent theme within sustainability science of the need to translate various knowledge into action that will have a meaningful societal impact (Miller et al., 2014). Ideally, the information and results of this research project will be useful in obtaining this impact.

Furthermore, the information and results presented herein can help answer some of the core questions for the future of sustainability science, in particular, the enabling of social and institutional learning for sustainable development (Miller et al., 2014). Remote sensing of the Chantry Dunes, including the results and outcomes of this current research project, can provide insights and knowledge that can result in a better understanding of the dune system, and how it has changed over time. The use of remote-sensing data can also provide numerous opportunities for community participation in the mapping exercise and facilitate local understanding of the various dynamic processes operating within the beach and dune environments. The knowledge and understanding generated through these processes can subsequently be used by local government, residents, and stakeholders to better assess dune management and make collective decisions regarding the sustainability of the dune system. Moreover, the methodologies used in this research project will also be useful in providing researchers with insight as to suitable research approaches to map and monitor coastal dune systems in the Great Lakes.

Lastly, this current research project will provide valuable information pertaining to the social, economic, and environmental functions of the Southampton waterfront. These complex and inter-related functions represent the three “pillars” or dimensions of sustainability and must be considered in a holistic and balanced manner when evaluating and implementing dune management and stewardship decisions. The management of the Chantry Dunes requires a delicate balance between addressing the needs of Southampton’s economy, local property owners, and the ecological health of the dune system.

1.5 - Thesis Layout

This thesis is organized into five chapters. To situate the research project within the broader literature, the following chapter discusses and reviews the existing literature on the use of remote

sensing in the mapping and monitoring of coastal dune vegetation. In particular, the chapter will examine the major themes, concepts, and trends on the use of remote sensing in dune vegetation research, including image classification and change-detection analysis. Chapter Three explains the data and methodological approaches used in the research project, including the data acquisition process, image preprocessing, and the analytical methods performed on the remotely sensed datasets. The results of the analytical methods performed and an analysis and discussion of these results are presented in Chapter Four. The thesis concludes with Chapter Five, which provides an overview of the research findings, and identifies potential areas for future research. Lastly, recommendations regarding management and stewardship approaches moving forward based on the results of this study are highlighted and discussed.

Chapter Two: Review of the Literature

2.1 - Introduction

The purpose of this chapter is to provide an overview of the literature relevant to this research project. This chapter is organized around several central themes and concepts important to the remote sensing of coastal dune vegetation, including the satellite and airborne sensors commonly employed, classification approaches and algorithms, and change-detection techniques. The chapter will conclude with a brief summary and analysis of the main themes and conclusions drawn from the literature reviewed.

2.2 - Satellite Sensors Used in the Remote Sensing of Coastal Dune Vegetation

The selection of the appropriate sensor(s) must receive careful consideration as it can greatly influence the production of accurate and useful information products. Advancements in sensor technologies and the increasing availability of multispectral and hyperspectral imagery provide a wide variety of sensor options. In determining which sensor to use, the spatial, spectral, radiometric, and temporal resolution of potential sensors must be considered. Spatial resolution is a measurement of spatial detail and refers to the smallest Earth-surface feature that can be detected by the sensor (e.g., 1 m, 30 m). Spectral resolution refers to “the specific wavelength intervals that a sensor can record” while radiometric resolution is a “measure of a sensor’s ability to distinguish two objects of similar reflectance” (Klemas, 2011, pg. 3). Lastly, temporal resolution is a measurement of how frequent a geographic area is visited by the sensor. As explained by Xie et al. (2008), there are four main related factors that may influence the selection of the most appropriate sensor including the research objectives, costs of image acquisition, climatic conditions, and technical issues (i.e., image quality, preprocessing requirements, etc.)

Satellite sensors employed in mapping and monitoring coastal sand dune vegetation include the Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM), and Landsat-7 Enhanced Thematic Mapper Plus (ETM+) (**Table 2.1**). Sensors onboard multispectral, high resolution satellite platforms including IKONOS and QuickBird have also been increasingly used in studying coastal dune vegetation (Timm and McGarigal, 2012; Özdemir et al., 2005; Berberoğlu, Alphan, and Yilmaz, 2003). Furthermore, airborne hyperspectral remote-sensing systems, such as the Compact Airborne Spectrographic Imager (CASI), have also gained popularity in recent years. These sensors typically operate in the visible and infrared portions of the electromagnetic spectrum (EMS), and detect and measure the reflectance of electromagnetic energy from Earth-surface features. Lastly, aerial photography and light detection and ranging (LiDAR) data have also been increasingly used in the remote sensing of coastal dune vegetation (Kempeneers et al., 2009).

Table 2.1: Comparison of the Commonly-Used Sensors in the Remote Sensing of Dune Vegetation

	Landsat MSS	Landsat TM	Landsat ETM+	IKONOS	QuickBird
Date First Launched	July 1972	July 1982	April 1999	Sept. 1999	Oct. 2001
Spectral Resolution (μm)					
Panchromatic (Pan)			0.52 - 0.9	0.45 - 0.90	0.45 - 0.90
Band 1		0.45 - 0.52	0.45 - 0.515	0.45 - 0.52	0.45 - 0.52
Band 2		0.52 - 0.60	0.525 - 0.605	0.52 - 0.60	0.52 - 0.60
Band 3		0.63 - 0.69	0.63 - 0.69	0.63 - 0.69	0.63 - 0.69
Band 4	0.5 - 0.6	0.76 - 0.90	0.75 - 0.90	0.76 - 0.90	0.76 - 0.90
Band 5	0.6 - 0.7	1.55 - 1.75	1.55 - 1.75		
Band 6	0.7 - 0.8	10.4 - 12.5	10.4 - 12.5		
Band 7	0.8 - 1.1	2.08 - 2.35	2.09 - 2.35		
Spatial Resolution	80 m	30 m (120 m for Band 6)	15 m (PAN) 30 m	1 m (PAN) 4 m	0.61 m (PAN) 2.44 m
Radiometric Resolution	6-bit	8-bit	8-bit	11-bit	11-bit
Temporal Resolution	16 - 18 days	16 days	16 days	3 - 5 days	1 - 3.5 days

(Source: DigitalGlobe, 2014a/b; Lillesand et al., 2008)

2.2.1 - Landsat MSS

The Multispectral Scanner (MSS), an across-track scanner, was first launched with the Landsat-1 satellite in 1972. The MSS on the first three Landsat missions provided images with a spatial resolution of 79 m, while the MSS on Landsat-4 and -5 had a spatial resolution of 82 m (Lillesand et al., 2008). The use of Landsat MSS was impacted by the launch of Landsat TM and Landsat ETM+, which provided greater spatial, spectral, temporal, and radiometric resolutions. The development of high spatial resolution sensors onboard satellite platforms, such as QuickBird and IKONOS, has resulted in the use of Landsat MSS being limited to change detection research where cost-effective, readily downloadable, and historical imagery is required (Maiti and Bhattacharya, 2011; Efe and Tagil, 2008; Alphan, 2005).

2.2.2 - Landsat TM and Landsat ETM+

The Landsat TM was launched with Landsat-4 (1982) and Landsat-5 (1984) (Jensen, 2005). The TM sensor has seven bands with a spatial resolution of 30 m, except for the thermal infrared band (band 6) which has a spatial resolution of 120 m. The TM provided significantly higher resolutions than the MSS and greatly increased the applications of remotely sensed data. Landsat TM data have been used to map diverse coastal vegetation communities in Australia (Yagüe and García, 2005) while other researchers including Efe and Tagil (2008) and Yaw Kwarteng and Al-Ajmi (1996) have effectively used Landsat TM data in change detection studies with much success.

The Landsat ETM+ was launched in April 1999. New features included the improved 60 m spatial resolution for the thermal infrared band and a 15 m panchromatic band covering a spectral range from 0.52 μm to 0.90 μm (Lillesand et al., 2008; Jensen, 2005). Given technological improvements and reduced costs, the Landsat ETM+ is one of the most commonly

employed sensors in the remote sensing of vegetation, including coastal dune vegetation (Xie et al., 2008; Efe and Tagil, 2008; Özdemir et al., 2005; Yagüe and García, 2005). The ETM+ has also been used in change detection research and often in conjunction with other sensors including the Landsat MSS, Landsat TM, and Satellite Pour l'Observation de la Terre or SPOT (Gonçalves et al., 2014; El-Asmar and Al-Olayan, 2013; Alphan, 2005). Landsat imagery has been used to accurately map vegetation, including coastal vegetation, at the broad community level. Due to its medium spatial resolution, the use of Landsat imagery in detailed habitat mapping or mapping of smaller coastal environments has proven to be difficult, especially in heterogeneous and complex environments (Klema, 2011; Xie et al., 2008; Özdemir et al., 2005).

2.2.3 - High Resolution Satellite Platforms (QuickBird, IKONOS)

The increasing availability and development of high spatial resolution sensors has revolutionized the field of remote sensing. IKONOS was launched in 1999 and acquires data in four bands covering the visible and NIR portions of the EMS with 4 m spatial resolution. In addition, IKONOS is equipped with a panchromatic band with a spatial resolution of 1 m. IKONOS has a radiometric resolution of 11-bits and a temporal resolution of less than three days (Jensen, 2005). In their study investigating agricultural encroachment on the coastal dunes of the Eastern Mediterranean in Turkey, Berberoğlu, Alphan, and Yilmaz (2003) used IKONOS imagery and historical aerial photography to detect changes in LULC since the mid-1970s and obtained an overall classification accuracy of 84%.

QuickBird was launched in October 2001 and has four bands covering the visible and NIR portions of the EMS with a spatial resolution of 2.44 m. The sensor also has a panchromatic band with a spatial resolution of 0.61 m. The radiometric resolution is 11-bit and the temporal resolution ranges from one to five days (Jensen, 2005). Timm and McGarigal (2012) used

QuickBird data in conjunction with multispectral orthophotography to accurately map coastal dune and salt marsh ecosystems at Cape Cod National Seashore. QuickBird imagery has also been employed in mapping and change analysis studies of terrestrial and aquatic vegetation on the Fire Island National Seashore with a high level of classification accuracy (Wang et al., 2007). In their study assessing the suitability of QuickBird and Landsat ETM+ data in the classification of dune vegetation in Turkey, Özdemir et al. (2005) concluded that QuickBird imagery, with an overall accuracy of 82.2% for 10 habitat classes, was more suitable for vegetation cover mapping than Landsat ETM+. However, the authors did note that further information from field data and inventories are required to further supplement QuickBird imagery.

2.2.4 - Hyperspectral Sensors (CASI)

Hyperspectral sensors acquire imagery in hundreds of narrow and contiguous spectral bands in the visible and infrared portions of the EMS. As these sensors collect hundreds of bands of data, they can be used to better discriminate between the reflection characteristics of various Earth-surface features that otherwise may be lost by sensors with broader bandwidths, such as the Landsat TM and ETM+ (Lillesand et al., 2008; Jensen, 2007). It is this characteristic of hyperspectral data that makes it particularly useful for differentiating between species and producing accurate vegetation maps (Xie et al., 2008). Hyperspectral sensors have also proven beneficial in collecting data that were restricted to site surveys or laboratory testing. Due to the benefits, hyperspectral imagery has been used in a diverse range of applications relating to water quality, vegetation type, plant stress, and surface mineralogy (Adam et al., 2010; Schmidt and Skidmore, 2003).

CASI is an airborne hyperspectral sensor that can acquire up to 288 bands of continuous data from the visible and near-infrared regions of the EMS (~ 0.4 and $1.05 \mu\text{m}$). A notable

advantage of the CASI includes its ability to be spatially and spectrally programmed to suit various applications (Lillesand et al., 2008; Jensen, 2005). In addition, the sensor is equipped with geo-correction software and can be mounted to ensure stability during data acquisition. Ideally, the acquisition of airborne hyperspectral data should be obtained in favourable conditions including calm winds, clear visibility, and in the late morning or early afternoon to maximize visibility and reduce glare. These considerations are paramount in obtaining quality data, and minimizing complications that may arise during data preprocessing and producing highly accurate outputs.

Shanmugam et al. (2003), Lucas et al. (2002), and Zhang et al. (2012) all have used CASI data to map coastal dune vegetation at Kenfig National Nature Reserve in the United Kingdom. Their findings indicate that CASI provides high classification accuracies (e.g., 85-90% or greater) that permit classifiers to better discriminate between the unique spectral responses of the diverse habitats present within coastal dune ecosystems. However, the complex composition of these ecosystems still presents challenges in the development of map products of use for conservation purposes (Shanmugam et al., 2003).

2.2.5 - Aerial Photography

Several studies have used aerial photographs to map and monitor coastal dune ecosystems (Hantson et al., 2012; Kempeneers et al., 2009; Dech et al., 2005; Berberoğlu et al., 2003; Brown and Arbogast, 1999). Aerial photographs have proven to be a valuable source of information regarding the temporal changes of phenomena over a large geographic area (Jungerius et al., 1992; Jungerius and van der Meulen, 1989). Manual interpretation of aerial photographs has been used to monitor the evolution of dune ecosystems and geomorphological processes (i.e.,

blowouts) occurring (see Geleen, 1997; Hartog et al., 1992); however, this approach can be a time-intensive and subjective endeavour (Lillesand et al., 2008).

Traditional aerial photographs typically represent complete reflectance data for a broad range of the electromagnetic spectrum encompassed in one band. Accordingly, the analysis of distinct spectral bands is not possible. Both Jensen (2005) and Lawrence et al. (1996) suggested that the procedure for scanning and processing images can be modified to result in a multispectral dataset with a minimum of three bands. This procedure was successfully adopted by Dech et al. (2005) to obtain multispectral data from colour aerial photographs of a Lake Huron sand dune system within Pinery Provincial Park (Ontario) and to classify land cover.

Both Hantson et al. (2012) and Kempeneers et al. (2012) used aerial photography in combination with LiDAR data to produce map products with overall accuracies of 60-70%. In these studies, the instruments used to acquire the aerial photographs also obtained multispectral data of the study sites, which were then used in subsequent classification and mapping initiatives. Berberoğlu et al. (2003) used monochrome aerial photographs acquired in 1976 and IKONOS imagery acquired in 2002 to assess changes in LULC on the eastern Mediterranean coastal dunes of Turkey. The 1976 aerial photographs were resampled to a spatial resolution of 4 m to ensure compatibility with the IKONOS imagery. Although the authors were successful in highlighting the role of texture techniques for the classification of high spatial resolution images, it was also noted that the scale of the aerial photographs did limit the level of detail provided in the change-detection analysis. This certainly highlights a limitation of using historic aerial photographs in that the researcher has little control over the spatial resolution of these images. Nevertheless, these historic images provide important temporal information of geomorphological and ecological processes occurring within these environs.

Brown and Arbogast (1999) investigated the feasibility of digital photogrammetric methods to study and manage dune systems. Panchromatic stereographic aerial photographs of Ludington State Park in Michigan from 1965 and 1987 were used, in addition to ground control points and digital elevation models (DEMs), to determine volumetric changes in sediment deposition during the 22 year time period. The authors concluded that dynamic dune systems can be monitored using digital photogrammetric techniques. One notable challenge was the establishment of a suitable network of ground control points that were stable across time, observable in the aerial photographs, and accessible on the ground; however, it was concluded that higher accuracies could be achieved with better and more stable ground control points (Brown and Arbogast, 1999).

2.2.6 - Airborne LiDAR

Light detection and ranging (or LiDAR) involves the transmission of laser light toward an Earth-surface feature from a known position and measurement of the elapsed time for the pulse to return to the sensor. This time is subsequently used to calculate the distance between the sensor and the Earth-surface feature to provide precise and high resolution position measurements. LiDAR is an active remote sensing system that can operate both during the day and night. Early applications of LiDAR in the 1970s included terrain modelling and bathymetry; however, the increasing availability of the technology due to increased cost-effectiveness has resulted in LiDAR being used for a wide variety of applications including forestry and coastal dune vegetation (Kempeneers et al., 2009; Lillesand et al., 2008). Hantson et al. (2012) and Kempeneers et al. (2009) have used LiDAR technology to map and monitor coastal dune vegetation in both the Netherlands and Belgium, respectively. Kempeneers et al. (2009) used LiDAR technology and multispectral data acquired from a digital camera to map coastal dune

vegetation in the Westhoek nature reserve, the largest coastal dune site in Belgium. To map the dune vegetation, the multispectral dataset was fused with the LiDAR data, improving the overall classification accuracy to 71%. While this may be lower than a standard acceptable level of accuracy (i.e., accuracy greater than 85%), the authors concluded that LiDAR has the potential to resolve spectral confusion between LULC classes.

Hantson et al. (2012) investigated whether vegetation height and an object-based classifier would improve the classification accuracy of invasive woody species in the coastal dunes of Vlieland, Netherlands. Using LiDAR data and high-resolution aerial photographs, the results showed vegetation height and the object-based classification increased the overall classification accuracy. It was therefore concluded that LiDAR data and object-based classification can be used to produce maps that provide enough useful detail for the management of invasive species in dune ecosystems.

2.3 - Remote Sensing of Vegetation

As discussed in Chapter One, Earth-surface features respond differently to various wavelengths of electromagnetic energy. The way a particular feature responds to a range of wavelengths across the electromagnetic spectrum can be used to determine the spectral response pattern of an Earth surface feature (**Figure 2.1**). For example, recall that due to the internal structure of plants, healthy vegetation strongly reflects NIR while absorbing visible red energy. Thus, in the remote sensing of vegetation, the red and NIR regions of the EMS are of particular interest, given that the unique spectral response patterns of vegetation can be used to discriminate between different vegetation types and between other Earth-surface features (Lillesand et al., 2008; Bannari et al., 1995). A notable characteristic of the spectral response pattern for healthy vegetation is the red edge, which is a sharp transition in reflectance in the NIR region of the

electromagnetic spectrum (approximately 0.7 μm). The unique spectral response patterns of healthy vegetation species in the red and NIR bands have been used as the basis for a number of vegetation indices. Vegetation indices use a mathematical combination of two or more spectral bands to quantitatively highlight certain properties of vegetation including vigour, condition, and other biophysical parameters (Jones and Vaughan, 2010; Campbell, 2007).

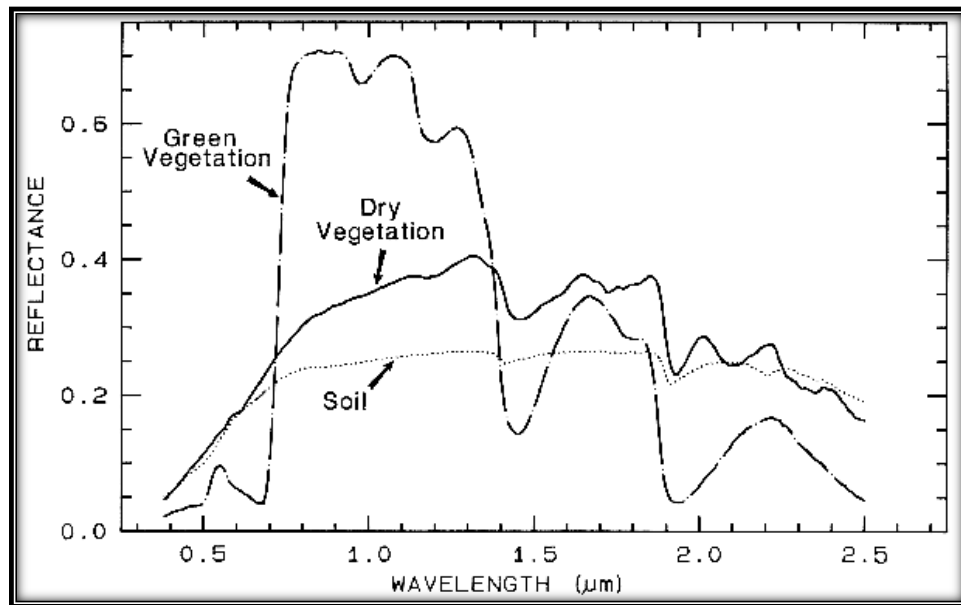


Figure 2.1: The spectral response patterns of green vegetation, dry vegetation, and soil. The red edge at approximately 0.7 μm is clearly visible. (Source: Clark et al., 2003).

While several vegetation indices have been developed to date, perhaps the most common index is the normalized difference vegetation index (NDVI), which is calculated using the following formula: $(\text{NIR reflectance} - \text{Red reflectance}) / (\text{NIR reflectance} + \text{Red reflectance})$. This equation produces an index value that ranges from -1, usually water, to +1 for healthy photosynthesizing vegetation (**Figure 2.2**). The index values can then be used to produce a NDVI image and subsequently used to inform management practices, produce vegetation vigour maps, and monitor vegetation change over time (Hugenholtz et al., 2012; Xie et al., 2008). One advantage of using the NDVI is that it greatly compensates for differences in sun illumination,

aspect, slope, and other variations in topography (Lillesand et al., 2008). In this regard, the NDVI can be beneficial given the topographic variability commonly present in coastal dune ecosystems that may present challenges for the production of accurate map products.

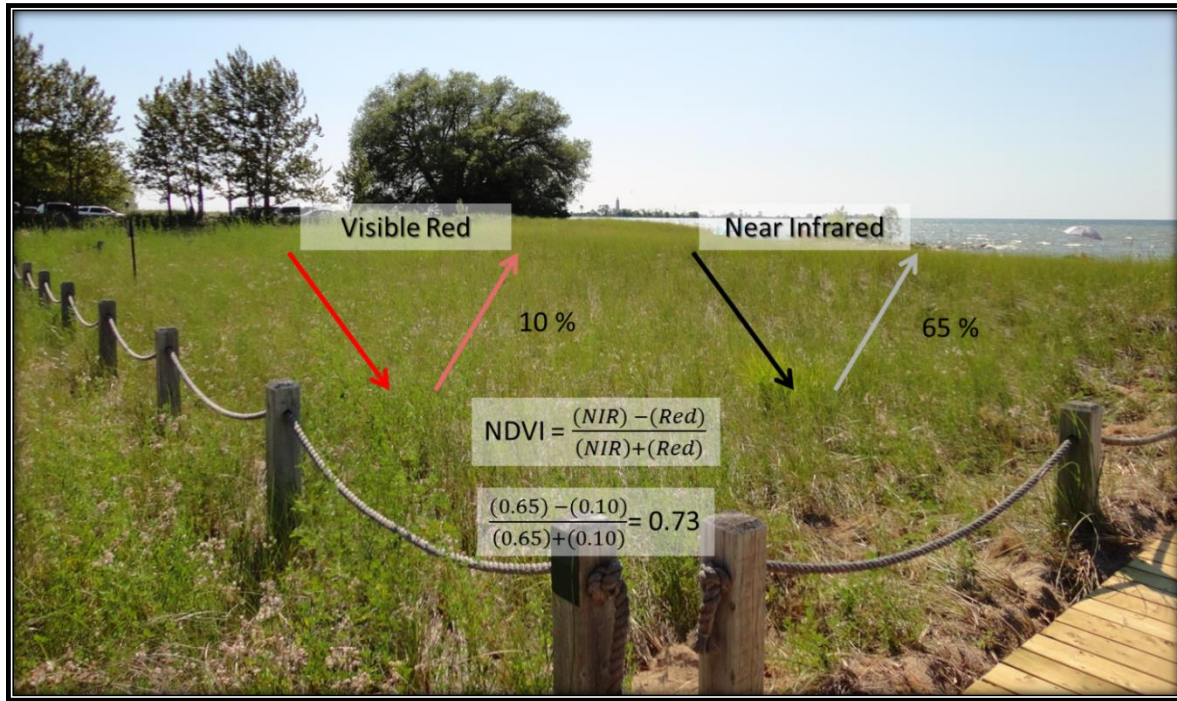


Figure 2.2: An example of a NDVI calculation for healthy, photosynthesizing dune vegetation. (Adapted from Shellito, 2014).

Overall, a major benefit of vegetation indices is the useful information they provide regarding the health of vegetation and their ability to identify disease or significant deterioration invisible to the naked eye (Canada Centre for Remote Sensing, 2008). In the context of coastal dune ecosystems, such information is important as the health of dune vegetation is directly related to the overall health of the dune system. This information can be used by coastal managers, governments, and stakeholders to develop co-ordinated and informed responses in an appropriate and timely manner.

2.4 - Classification Techniques to Map and Monitor Coastal Dune Vegetation

A common image-analysis technique in the remote sensing of coastal dune vegetation is image classification, which may be defined as an automated process whereby useful thematic information, such as LULC classes, is extracted from remotely sensed data. The overall objective of this process is to classify each pixel into a particular LULC class or theme based on the spectral characteristics of the respective pixel (Lillesand et al., 2008). There are two main types of image classification: supervised and unsupervised. Both image classification types have been used in the remote sensing of coastal dune vegetation and there are benefits and disadvantages to both (Xie et al., 2008; Lillesand et al., 2008; Jensen, 2005). The decision to use a supervised or unsupervised classification approach may be influenced by several factors, including, but not limited to, the resolution of the image and the complexity of the area under investigation (Jensen, 2005). A review of the literature reveals that supervised, unsupervised, and soft classification approaches have all been used to map and monitor coastal dune ecosystems (e.g., Özdemir et al., 2005; Shanmugam et al., 2003; Lucas et al., 2002).

2.4.1 - Supervised Image Classification

Supervised classification involves the automatic categorization of image pixels into LULC classes and may be characterized by three distinct stages, including training, classification, and output (Lillesand et al., 2008). In the training state, the analyst is “training” the classification algorithm by selecting sites in the image that are homogenous examples of known LULC types present. These sites are known as training sites or calibration sites because the spectral characteristics and response patterns of these areas are used by the image classification algorithm to classify the remaining pixels in the image. Selection of training sites is usually informed by ancillary data including aerial photographs, maps, *in-situ* data, and familiarity with the study site

(Klemas, 2011). Next, the classification stage consists of the algorithm using the statistical parameters and spectral response patterns of the training sites to identify similar spectral characteristics and classify pixels accordingly. Finally, the output stage involves the presentation of the results, such as the creation of thematic maps; results may also be imported into a geographic information system (GIS) for spatial analysis (Lillesand et al., 2008; Jensen, 2005).

Before the results are presented in the output stage, it is critical that an accuracy assessment is performed to determine the overall correctness of the classification results. Accuracy assessment, which involves both qualitative and quantitative components, compares the unknown quantities of the image classification to a specific norm assumed to be correct (Campbell, 2007). Thus, the closer the classification result to the norm, the higher the accuracy. Accuracy assessment is an integral aspect of the classification stage as it not only informs the image analyst of the level of correctness, but can also be utilized to identify areas for improvement that can be implemented in subsequent classification initiatives to further improve accuracy (Lillesand et al., 2008).

There are various supervised classification algorithms that may be used in image classification although the most common in mapping coastal dune vegetation are minimum distance and maximum-likelihood (Malatesta et al., 2013; Hantson et al., 2012; Xie et al., 2008; Shanmugam et al., 2003). The selection of a classification algorithm is dependent on a variety of factors including the characteristics of the data, the complexity of the ecosystem, and the desired output (Jensen, 2005). The minimum distance algorithm (**Figure 2.3**), one of the simpler classification algorithms, calculates the class means based on the training data and then assigns unknown pixels to the closest class. The analyst can also set a distance threshold; in cases where pixels are farther than this specific distance from any class mean, the pixels are classified as

‘unknown’ (Lillesand et al., 2008). As the minimum distance classifier does not use covariance information, it is useful in dune ecosystems which are often characterized by their high spatial heterogeneity (Klemas, 2011). In the remote sensing of coastal dune systems, the minimum distance algorithm has proven to yield high classification accuracies. Shanmugam et al. (2003) applied the minimum distance algorithm to CASI data to produce a habitat map (with 10 habitat classes) of the Kenfig National Nature Reserve in the United Kingdom that yielded classification accuracies greater than 90%.

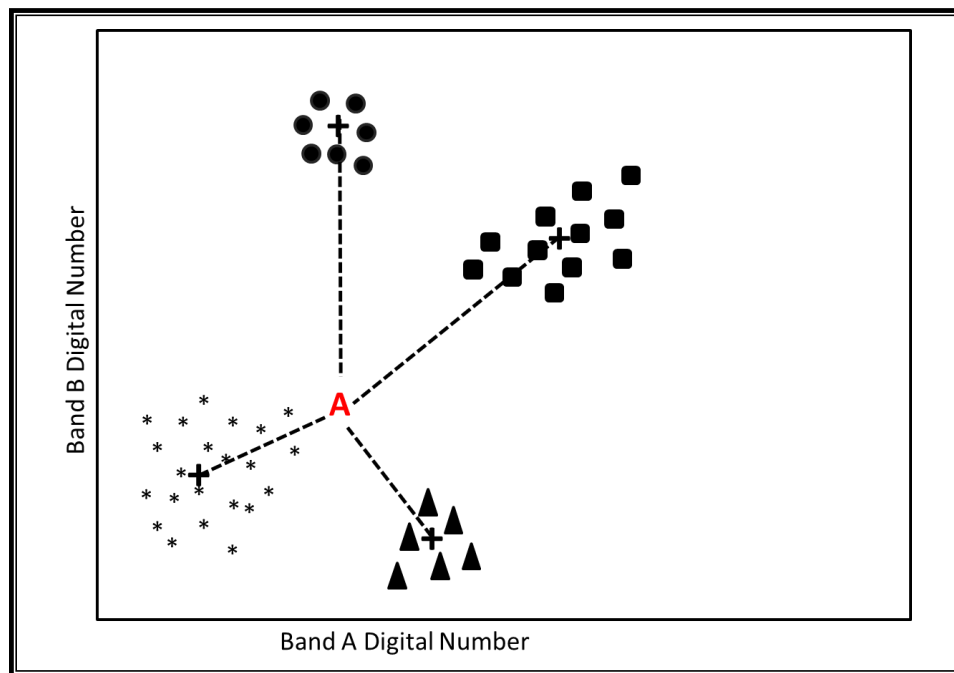


Figure 2.3: The minimum-distance classification algorithm calculates the class means based on the training data and then classifies unknown pixels to the closest class. (Adapted from Lillesand et al., 2008).

The maximum-likelihood algorithm incorporates the mean values and covariance of training classes to construct equiprobability contour regions (**Figure 2.4**). Unknown pixels that fall into these decision regions are classified to that specific class while overlapping pixels or

those residing outside decision regions are labelled ‘unclassified.’ Malatesta et al. (2013), Hantson et al. (2012), Özdemir et al. (2005), Shanmugam et al. (2003), and Berberoğlu et al. (2003) all have used the maximum-likelihood algorithm in their respective studies with varying degrees of success. Shanmugam et al. (2003) applied the maximum-likelihood, minimum distance, and Mahalanobis distance classification algorithms to CASI data of the Kenfig National Nature Reserve in the United Kingdom to assess the ability of the algorithms to map the various levels of the National Vegetation Classification (NVC) scheme. The maximum-likelihood classification yielded an accuracy of 81.3% when mapping 10 habitat classes, which corresponded to level I of the NVC scheme. In comparison, the minimum distance and Mahalanobis distance algorithms achieved accuracies of 92.4% and 84.5%, respectively. Overall, the post-classification accuracy assessment indicated that as the number of habitat classes increased, the classification accuracy decreased. This is not surprising, however, given the tendency for classification accuracies to decrease as the number of LULC classes increases (Lillesand et al., 2008).

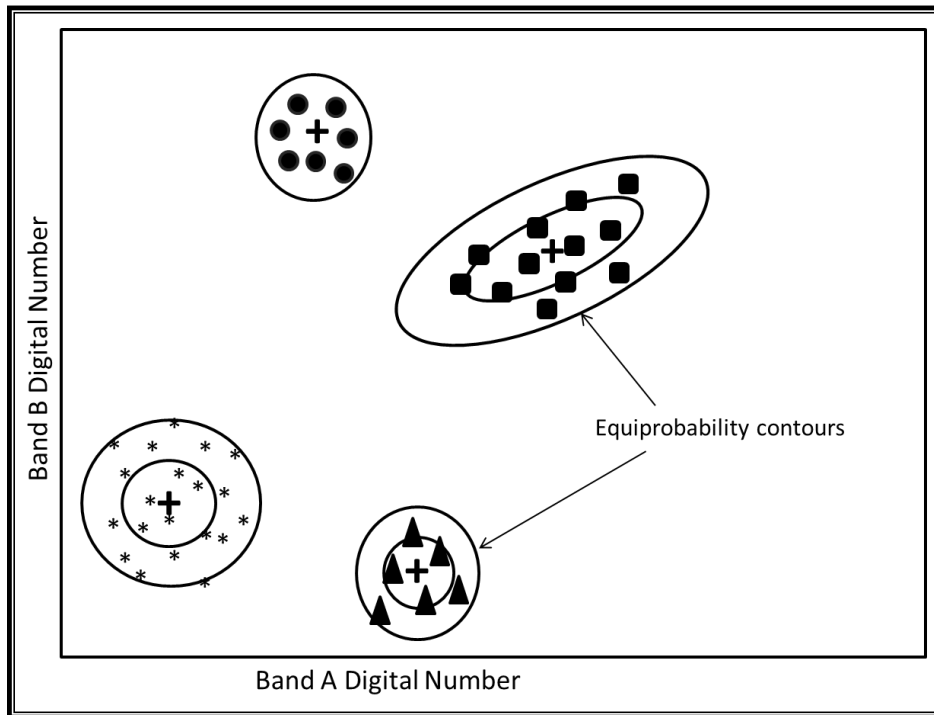


Figure 2.4: The maximum-likelihood algorithm uses the mean values and covariance of training classes to construct equiprobability contours. (Adapted from Lillesand et al., 2008).

Özdemir et al., (2005) applied the maximum-likelihood algorithm to Landsat 7 ETM+ data to determine its suitability in mapping dune vegetation on the Mediterranean coast of Turkey. The overall accuracy of the classification result was 75.7% for 7 habitat classes, which is deemed an acceptable level of accuracy for a national forest inventory. To provide context for this classification result, it is important to note that the coarser resolution of Landsat ETM+ data and the heterogeneity of the ecosystem under investigation greatly contributed to the lower accuracy results. Nonetheless, the authors concluded that the classification results could be used to monitor the dune vegetation at a broad scale level.

In their study of the heterogeneous arid environments of Socotra Island, Yemen, Malatesta et al. (2013) compared two different image classification approaches: the sequential maximum *a posteriori* (SMAP) classification and the maximum-likelihood classification. These

classification approaches were applied to a RapidEye image, with a spatial resolution of 5 m and five spectral bands, to map a total of 28 habitat classes. The SMAP yielded a classification accuracy of 87% while the maximum-likelihood classification resulted in what the authors called a ‘patchy map’ with an accuracy of 66%. Accordingly, this low classification accuracy result highlighted the algorithm’s inability to distinguish between the complex landscapes within the context of the study area. The authors concluded that the SMAP classification method was more appropriate for mapping the complex heterogeneous vegetation landscapes of Socotra Island and for the production of mapping products for conservation and sustainability initiatives.

Researchers have also used the maximum-likelihood algorithm in conjunction with additional remote-sensing data, such as LiDAR data, to improve the accuracy of coastal vegetation mapping and monitoring. Hantson et al. (2012) examined whether additional height information from LiDAR data combined with the maximum-likelihood algorithm could increase the classification accuracy of woody species in the dunes of Vlieland, Netherlands. Hantson et al. (2012) employed three classification methods including: (1) the maximum-likelihood algorithm using aerial photographs; (2) the maximum-likelihood algorithm combined with LiDAR data; and (3) object-based classification. Overall accuracy of the maximum-likelihood classification with aerial photographs was 38.7%, although the producer’s and user’s accuracy varied considerably based on species. The combination of height information from LiDAR data to the maximum-likelihood classification increased the overall accuracy to 50.4%. Lastly, object-based classification achieved an overall classification accuracy of 60%. This study concluded that the object-based classification could be used to produce maps with useful detail for the management of invasive species within dune ecosystems. Thus, image classification of coastal dune

environments can be improved with object-oriented classification approaches in combination with ancillary information.

Berberoğlu et al. (2003) applied the maximum-likelihood classification algorithm to a 2002 IKONOS image of the Eastern Mediterranean coastal dunes of Turkey. The integration of spectral information and variogram texture information increased the overall classification accuracy to 84%. The study concluded that the incorporation of textural information into classification approaches can maximize the accuracy of the agricultural and semi-natural vegetation land-cover classes in the eastern Mediterranean coastal dunes.

2.4.2 - Unsupervised Image Classification

Unsupervised classification, also known as clustering or cluster analysis, is the process whereby image pixels with similar spectral characteristics are grouped by the computer algorithm into unique clusters (or spectral classes) based on statistical criteria determined by the analyst. In contrast to supervised classification, unsupervised classification does not use training sites as the basis for classification and thus requires minimal input from the analyst. Unsupervised classification assumes that pixels within a particular LULC class will be clustered closely together in multispectral feature space. *A posteriori*, spectral classes (or clusters) are then assigned by the image analyst into thematic information classes of interest (i.e., urban, forest, wetland; Jensen, 2007). This may prove challenging given that some spectral clusters may represent mixed pixels, or may be spectrally similar to another cluster(s). In addition, the algorithm may also have identified “sub-classes” of LULC types that may (or may not) be of interest to the analyst; these may need to be combined into broader classes by the analyst (i.e., turbid water vs. clear water; Lillesand et al., 2008).

A number of clustering algorithms have been developed with two common algorithms being the K-means and the Iterative Self-Organizing Data Analysis Technique (ISODATA), which is a variant of the former (Schowengardt, 2007). The ISODATA algorithm will be discussed in further detail below given its use in the remote sensing of coastal dune vegetation (Efe and Tagil, 2008; Alphan, 2005). Prior to applying the ISODATA algorithm, the analyst inputs threshold parameters, including the maximum number of clusters to be identified, the minimum number of members in a cluster (expressed as a percentage), the minimum Euclidean distance between the means of the clusters, and the number of iterations. In contrast to the K-means algorithm, which initially allocates mean vectors based on analysis of the first row of image pixels, the ISODATA algorithm begins with an arbitrary cluster allocation based on the statistics of each band to be used in the classification process. Each image pixel in the remote sensing dataset is compared to each cluster's mean and then assigned to the cluster whose mean is the closest. During each iteration, the number of clusters can be changed by merging, splitting, or deleting clusters (Lillesand et al., 2008; Xie et al., 2008; Jensen, 2005). For example, if the distance between the means of two clusters is less than a predefined distance specified by the analyst, the clusters are merged together. Conversely, if the standard deviation of a cluster exceeds a predefined parameter, the clusters are split. The iterative process continues until the statistics of the clusters do not exceed specified parameters or the maximum number of iterations has been reached. The successful application of these unsupervised classification approaches is dependent on the analyst's understanding of each algorithm and their knowledge of the area under investigation (Lillesand et al., 2008; Jensen, 2007).

Unsupervised classification algorithms, including the ISODATA algorithm, have been used in the remote sensing of coastal dune ecosystems. Efe and Tagil (2008) applied the

ISODATA algorithm to three Landsat images from 1972, 1987, and 2000 to observe changes in LULC type around Lake Tuz on the Seyhan Delta. A total of nine main classes, including sea, natural grassland, sparsely vegetated area, and beaches, were mapped with a classification accuracy of more than 70%. The ISODATA algorithm has also been used in conjunction with other image analysis procedures, including change detection. In his study examining the coastline changes in river deltas on the southeast Mediterranean coast of Turkey, Alphan (2005) classified two Landsat images acquired in 1972 and 2002 into 12 thematic classes using the ISODATA algorithm. The clusters in these two maps were then assigned either “land” or “water” classes in order to facilitate subsequent pixel-based change-detection analysis.

2.4.3 - Soft Classification Approaches

The supervised and unsupervised classification algorithms highlighted in sections 2.4.1 and 2.4.2 are examples of ‘hard classifiers,’ which involves each pixel in an image being assigned to one land-use/land-cover class. However, this is often not a true representation of the complexity and heterogeneity of many environments as there may be more than one LULC class present within a pixel. These are known as mixed pixels or ‘mixels.’ The presence of mixels in an image, especially those in images with medium to coarse spatial resolution, can result in decreased classification accuracy as their spectral characteristics do not represent any particular LULC class. Accordingly, the effectiveness of mapping outputs may be impacted. To address these issues and concerns soft classification or sub-pixel classification techniques, such as spectral mixture analysis (SMA) and fuzzy classification, have been developed to overcome the problem of mixels and improve the accuracy of image classification and information outputs (Lillesand et al., 2008; de Lange, 2004). These classification techniques have proven to increase the

accuracies of map outputs which can then be effectively used by a variety of users (Hugenholtz et al., 2012; Xie et al., 2008; Lucas et al., 2002; Zhang and Foody, 1998).

Fuzzy classification techniques are based on the concept of fuzzy logic, which accounts for the heterogeneity of Earth's surface and posits that many LULC types do not adhere to hard boundaries but gradually transition from one to the other. Thus, rather than assigning only one LULC class to a pixel, fuzzy classifiers describe the relative proportion of a particular LULC class present within a pixel. This can result in a more accurate presentation of reality and in the extraction of more accurate thematic information (Foody, 2002). Fuzzy classifiers still require training, although the analyst may select areas that are more heterogeneous to better understand the area and to create more accurate map outputs. A major advantage of fuzzy classification is that the analyst can "obtain information on the various constituent classes found in a mixed pixel" (Jensen, 2005, pg. 389). For example, a pixel may have the following values: dense forest = 0.70, water = 0.20 and urban = 0.10. It is important to note that all the values for each pixel must total 1.0. The analyst can then use this information, for example, to create maps that show only pixels that have a dense forest value >65% and a water value >15%. Another fuzzy classification approach is fuzzy clustering, which is similar in concept to the K-means unsupervised classification algorithm. However, rather than establishing hard boundaries in multispectral feature space, fuzzy regions are created. Next, membership grade values are assigned to describe how close a particular pixel is to the means of all LULC classes (Lillesand et al., 2008).

Spectral mixture analysis (SMA) is another popular soft classification technique whereby the spectral signatures of mixed pixels are compared to sets of pure reference spectra known as endmembers. It is assumed the spectral signatures of mixed pixels are a variation of a limited

number of Earth-surface features present in an image (Lillesand et al., 2008). The overall objective of SMA is to unmix the mixed pixels in order to determine the relative proportions of the spectral endmembers which combine to produce the spectral signature of the mixed pixel (Jensen, 2005). This information can then be used to develop a more accurate estimation of the LULC classes present in an image scene and result in a more descriptive representation of reality and the further extraction of accurate thematic information. It is important to highlight some limitations and challenges associated with SMA. First, the validity of SMA is dependent on the identification of all endmembers present in an image scene. However, the identification of accurate endmembers may prove difficult, especially if the image scene is complex. To address these challenges, a number of methods have been developed including the use of laboratory reflectance spectra and spectral libraries (Schowengerdt, 2007).

Several studies have used soft classification techniques to map and monitor coastal dune vegetation. Lucas et al. (2002) applied the linear mixture model and fuzzy-c means clustering to CASI data to produce a habitat map of the Kenfig National Nature Reserve in South Wales, United Kingdom. Both the linear mixture model and fuzzy c-means clustering are examples of soft classification approaches that may be used in the classification of mixed pixels. The authors concluded that both soft classification approaches could be used to effectively map sand and vegetation at the sub-pixel level within the Kenfig National Nature Reserve. In another study of the coastal dunes in the Kenfig National Nature Reserve, Zhang et al. (2012) applied a combination of the linear mixture model and the maximum-likelihood classification algorithm to archived CASI data. First, a linear mixture model was applied to determine the sub-pixel abundance of soil, green vegetation, and non-green vegetation. A maximum-likelihood classification algorithm was then applied separately to identify mixed pixels believed to contain

a mixture of the two functional vegetation types present. This was then used to transform the results of the linear mixture model to separate the two functional vegetation types and bare sand. Classification accuracies of 82.7% and 98.2% were achieved for the linear mixture model and the maximum-likelihood algorithm (four classes mapped), respectively. To provide context for these classification accuracies, it is important to note that the accuracy assessment of these results was limited by a lack of recent ground truth data. However, the authors concluded that hard classification approaches can be used to interpret results from the linear mixture model and separate different functional vegetation types present in an image scene.

In their assessment of remote-sensing techniques for mapping coastal dune ecosystems, Shanmugam et al. (2003) concluded that sub-pixel classifiers can produce map outputs that are more useful for conservation managers, although hard classifiers can also be used to produce effective maps that are easy to read and understand. Thus, the authors argued that results from both hard and soft classifiers can be used in the production of baseline maps to facilitate conservation management programs. The literature reveals that the output maps with the most potential and usefulness for dune conservation management involve the subsequent application of soft classifiers after hard classification has been performed (Hantson et al., 2012; Xie et al., 2008; Shanmugam et al., 2003).

2.5 - Change Detection

Increasing access to historical satellite and airborne data, and recent developments in satellite and airborne sensor resolutions has facilitated the growing popularity of change detection research studies in remote sensing, particularly in ecosystem monitoring (Coppin et al., 2004). Change detection is a common and important image analysis technique which involves the use of multi-temporal remotely sensed data to identify differences in LULC (Lillesand et al, 2008). The

basic premise is that changes in LULC will result in changes in reflectance values. Other factors such as sun angles, atmospheric conditions, and phenological cycles may influence reflectance values; however, these can be controlled for example, by using images acquired on anniversary dates with little to no cloud cover and data from similar sensors. Moreover, it is important that the images are co-registered to within $\frac{1}{4}$ to $\frac{1}{2}$ pixel as the misregistration of pixels can result in erroneous classification and change detection errors (Lillesand et al., 2008; Lu et al., 2004; Townshend et al., 1992).

There have been many change-detection techniques developed to qualitatively and quantitatively assess LULC change, including temporal image differencing, vegetation index differencing, and post-classification comparison (Jensen, 2005; Lu et al., 2004; Singh, 1989). In temporal image differencing, the brightness values (BVs) of a pixel in one image are subtracted from those in another image ($\text{Image}_A - \text{Image}_B = \text{Difference Image}$). Image pixels with little to no change will yield small values approaching zero, while pixels with significant change will result in large values that are either positive or negative. While temporal image differencing is computationally simple, it does not provide “from-to” change classes. While the process will yield the difference in brightness values between the image dates, it will not indicate how the LULC type has changed over time (e.g., the image pixel has gone from being classified as “forest” to “urban”). Vegetation index differencing is conceptually similar to temporal image differencing; however rather than comparing the brightness values of a pixel on two image dates, the vegetation index values (e.g., NDVI) are compared. For example, the NDVI can be separately calculated for each pixel on two image dates (Image A and Image B). Next, the change in NDVI values for the two image dates can be computed by subtracting the NDVI value in Image B from the NDVI value in Image A ($\text{NDVI}_{\text{Image A}} - \text{NDVI}_{\text{Image B}} = \text{NDVI}_{\text{Change}}$).

Vegetation index differencing is easy to compute, provides emphasis in the spectral response patterns of various Earth-surface features, and may reduce the effects of topography and illumination. However, this technique does not provide “from-to” change classes, requires familiarity with the study area, and may enhance random noise, thus making image interpretation difficult (Lu et al., 2004).

In post-classification comparison, supervised or unsupervised image classification is performed on two images of the same geographic area but acquired on different dates (i.e. Image A and Image B). The pixels are then compared on a pixel-by-pixel basis using a change matrix to determine “from-to” change (Lillesand et al., 2008). It is important to note, however, that the success of the post-classification comparison technique is dependent on the classification accuracy of the classified images used (Lu et al., 2004). The comparison of images with inaccurate classifications will produce erroneous change detection results. While the aforementioned change-detection techniques are among the most prevalent in the remote sensing literature, they are by no means an exhaustive list. Change-detection technique research continues to be a topic of interest in the field of remote sensing and, while each approach has its own advantages and disadvantages, not one approach exists that may be universally applied to all cases (Lu et al., 2004).

There are several studies that have employed change-detection techniques to study coastal dune systems, including Gonçalves et al. (2014), Dech (2005), Yagüe and García (2005), Brown and Arbogast (1999), and Kwarteng and Al-Ajmi (1996). Alphan (2005) used pixel-based comparison to compare two maps generated from 1972 Landsat MSS data and 2002 Landsat ETM+ data of the Cukurova Deltas on Turkey’s southeast Mediterranean coast. After both images were classified using unsupervised classification approaches, a pixel-based comparison

of land and water areas between the two dates was performed. This comparison consisted of overlay analysis which involved overlaying one map onto the other and calculating the number of pixels that have the same and different values in the two image dates. Overlay analysis resulted in the pixels being labelled as ‘no-change’, ‘land-to-water’, or ‘water-to-land’ to produce a change map. While changes in LULC were attributed to both natural and anthropogenic factors, the author concluded the intensive growth and competition of the agriculture and industrial sectors significantly decreased the extent and overall quality of the coastal dunes. Lastly, in regards to the usefulness of remote-sensing technologies being used to monitor coastal changes, Alphan (2005) noted that hybrid data sets, including aerial photographs and satellite imagery, may provide additional information to improve the overall quality of change detection results.

In their study monitoring the coastal sand dunes on the Portuguese coast, Gonçalves et al. (2014) used free multi-temporal Landsat imagery (ETM+) and the Operational Land Imager (OLI) from 2000, 2002, 2013, and 2014 to examine coastal change. The four images were pansharpened to achieve a spatial resolution of 15 m while maintaining the spectral resolution of the respective images. To extract the shoreline in each image date, the Modification of Normalized Difference Water Index ($MNDWI = ((Green - MIR) / (Green + MIR))$) and the K-means unsupervised classification algorithm were applied. Next, the shoreline in each image was smoothed using an automated smoothing procedure. To extract the sand dunes for each image date, an image composed of five synthetic bands was created. The first band consisted of the MNDWI; the second band consisted of the NDVI; the third band comprised the Normalized Difference Built Up Index ($NDBI = ((MIR - NIR) / (MIR + NIR))$); the fourth band consisted of the first principal component (PC1) for each image date; and lastly, the fifth band was comprised

of the second principal component (PC2) for each image date. The fourth and fifth bands involved principal component analysis (PCA), which could be defined as “a technique that transforms the original remotely sensed dataset into a substantially smaller and easier-to-interpret set of uncorrelated variables that represents most of the information present in the original dataset” (Jensen, 2005, pg. 298). The goal of PCA is to reduce overall redundancy in remotely sensed datasets. PC1 accounts for the largest percent of total variance while additional components (i.e., PC2 and PC3) each contain a decreasing amount of total variance (Lillesand et al., 2008). The K-means unsupervised classification algorithm was then applied to obtain the primary sand dune class clusters. An online Web Map Service for Remote Sensing Imagery provided by Google Satellite and Bing Aerial were then used by Gonçalves et al. (2014) to facilitate the reclassification of the classified images so that each image was classified using the same LULC classes. This resulted in the seven thematic classes, including water, primary sand dunes, bare sand, bare soil, and vegetation. A qualitative analysis of the generated images revealed that the sand dunes have undergone considerable erosion during the 14-year time period. This study highlighted how the use of free remote sensing imagery (i.e., Landsat ETM+ and OLI) can be used in the implementation of an effective coastline monitoring system. However, while this methodology may prove useful in the monitoring of large coastal sand dunes and coastal environments, the effective monitoring of dune environments that are small in geographic area are likely to require high-resolution remotely sensed data, which is not freely available through online sources.

Change-detection techniques can also be applied to aerial photographs. Brown and Arbogast (1999) used two panchromatic stereographic aerial photographs (1965 and 1987) over Ludington State Park, Michigan, to determine the change in coastal dune topography over the

22-year time period. Digital elevation models (DEMs) were constructed using stereo models and post-processed differential global positioning system (GPS) ground control points. The two DEMs were then compared to construct maps of elevation change and, ultimately, to determine the approximate fluctuation of sand volume over the time period. The change analysis revealed that although the volume of sand likely increased, some locations experienced significant loss of sand volume and some blowouts deepened and enlarged. The findings demonstrate that aerial photographs can be used to effectively monitor the direction of sand drifting and changes in LULC over time.

Dech et al. (2005) used colour aerial photographs to investigate and quantify the changes in blowouts in Pinery Provincial Park, Ontario from 1973 to 1998. Multispectral data were extracted from the two aerial photographs and then classified using the maximum-likelihood classification algorithm with an overall classification accuracy of 90%. The land-cover types used in the supervised classification included water, sand, and vegetation (herbaceous and woody). The 1973 and 1998 classified maps were then imported into a GIS to identify changes in land-cover over the 25-year time period. Unchanged pixels between the two dates were classified into “stable categories,” while those pixels that changed were classified as either “establishment of herbaceous or woody vegetation on bare sand (colonization)” or “bare areas created by erosion or burial of previously vegetated areas (retrogression)” (Dech et al., 2005, pg. 171). This information was then used in the production of a change analysis map to identify the temporal changes in land-cover. Ten blowouts were identified in the change analysis map. Next, the perimeter of the 1998 blowouts was then traced and overlaid onto the change analysis map and the area of stable and change categories were measured in metres squared. The total net change in each blowout was calculated as the difference between total regression and total colonization.

Change-detection analysis revealed that the ten blowouts experienced considerable change, including both colonization and retrogression, during the time period investigated. Between 1973 and 1998, the total area colonized was 4,127 m² while the total bare area created was 3,991 m². The authors concluded that both colonization and retrogression were naturally co-occurring processes in the dune system and methodology employed highlights how aerial photographs can be a cost-effective alternative to other forms of remotely sensed data.

Several studies have used multi-temporal NDVI images to monitor vegetation change in dune environments. Kwarteng and Al-Ajmi (1996) used NDVI images (1987 and 1993) in a selective PCA procedure to detect and map vegetation change in southern Kuwait between 1987 and 1993. The selective PCA procedure resulted in the production of two principal components. The first principal component (PC1) represented information that was common to both the 1987 and 1993 images (i.e., topographic information), while the second principal component (PC2) consisted of the temporal contrast between the two images. Given PC2 accounted for 19.82% of the total variance, it permitted the authors to quantify the vegetation increase and decrease at 19.82%. From these two NDVI images, it was observed that vegetation did increase with a majority of the vegetation increase occurring within Kuwait City. Other desert areas characterized by active and smooth sand sheets experienced little to no change in vegetation. The authors' conclusions were supported by rainfall data during the respective dates, which indicated an approximate threefold increase in precipitation. Despite increased rainfall, the impact of the 1991 Gulf War, including the burning of oil lakes within the region, did have adverse impacts on vegetation in some areas. Overall, the authors concluded that the NDVI can be used to effectively map and detect vegetation change.

The use of NDVI images to monitor dune vegetation change has also been used in the Myall Lakes district region located on the central coast of New South Wales in Eastern Australia. The dune systems in the area are home to a diverse and unique range of vegetation communities. Yagüe and García (2005) produced NDVI images for 1993 Landsat TM and 2001 Landsat ETM+ data respectively. The Landsat TM data were acquired in November 1993 while the Landsat ETM+ data were acquired in August 2001. A main objective of the study was to highlight seasonal and temporal changes in vegetation and determine the utility of Landsat data for discriminating between the diverse association of plant species prevalent in the region for both the dry and humid seasons. To determine the NDVI change from 1993 to 2001, the authors performed NDVI image differencing—a process whereby the “before” image (1993) was subtracted from the “after” image (2001). The result was an image where vegetation increases were denoted by brighter tones, while vegetation decreases were denoted by darker tones. Major results of this image analysis included an increase in coastal sedimentation and higher NDVI values in the Bridge Hill Ridge area, where mineral exploration historically occurred but has since been restored. An increase in the urban LULC in the Forster-Tuncurry area was also observed between the two respective dates. While a majority of the plant associations had distinct seasonal NDVI values, the two main eucalypt associations in the region possessed similar phenological activity in both the spring and summer. Interestingly, a possible explanation for this may be the secretion of resin, described as “iridescent when wet” by damaged plants (Yagüe and García, 2005, pg. 359). The authors again noted that the use of multi-temporal NDVI data can provide valuable information about common vegetation associations and their phenological characteristics. Moreover, such information can prove useful in the production of accurate LULC mapping outputs.

2.6 - Summary and Conclusions

A review of the relevant literature indicates remote-sensing data can provide unique and valuable information regarding the spectral characteristics and spatial extent of coastal dune vegetation. While a number of challenges exist, including improving the classification accuracies of information outputs, the development of sensor technology and an increasing awareness of the procedures and methodologies available to researchers, offers exciting new opportunities for research.

As highlighted, there are a diverse range of sensors being used to study coastal dune vegetation around the world, including Landsat (TM and ETM+). In addition, as a result of the increased availability and affordability of high resolution imagery acquired by sensors, such as QuickBird and IKONOS, it is increasingly being used to develop information outputs with high levels of accuracy that are more useful for conservation and management purposes. Researchers have also used data from hyperspectral airborne sensors, such as CASI, with much success in the provision of higher classification accuracies. Aerial photographs and LiDAR technologies have also been used to augment satellite imagery and improve the ability to effectively map and monitor dune vegetation. While high resolution satellite platforms and LiDAR may provide improved classification and mapping capabilities, there are drawbacks, including large datasets and high data acquisition costs. The increased availability and affordability of Landsat imagery has facilitated its use in a variety of research projects pertaining to coastal dune vegetation. While this has proven beneficial for many dune systems, the use of Landsat imagery may not be feasible if the dune system under investigation is small or biologically complex, due to the coarser spatial and spectral resolutions of Landsat data. Overall, the selection of a suitable sensor

is dependent on numerous factors including the level of mapping accuracy required, the complexity of the dune environment, the size of the study area, and financial limitations.

Image classification is a popular analysis technique in the mapping and monitoring of coastal dune vegetation and is used primarily in the production of LULC maps for conservation and management purposes. However, the production of accurate maps suitable for these purposes can be challenging using hard classifiers, especially in complex heterogeneous dune environments where more than one LULC class may be present within an individual pixel. Accordingly, the use of soft classification approaches has proven useful in this regard and can provide a more realistic representation of the LULC classes present.

A variety of techniques have been used to detect and monitor change in coastal dune vegetation, including post-classification comparison and vegetation index differencing. The importance of acquiring images near anniversary dates to account for phenological and seasonal differences cannot be overstated. Moreover, images should be co-registered, as a failure to do so can result in erroneous change detection results. The availability of remotely sensed datasets and the relative infancy of high resolution sensors may impose limitations on the time period for which change-detection analysis can be performed. Nevertheless, the use of aerial photographs to perform change-detection analysis has been used with much success when satellite imagery was unavailable or lacking sufficient spatial and spectral resolutions.

Although several analytic approaches are described in the literature, it is important to note that these approaches cannot be generalized and assumed to be universally applicable to all geographic locations. This presents a unique challenge to researchers in identifying which methods work under certain circumstances to provide the most consistent and accurate results.

Accordingly, each analyst must determine the appropriate data analysis techniques that are most suitable for their study area after considering a variety of factors, including the research goals and objectives, heterogeneity of the study site, and the resolution of the remotely sensed data being employed. Further detail and rationale regarding the methodologies used in this research project is found in Chapter Three.

Many coastal dune systems have been studied around the world, including those in the United Kingdom, Mediterranean, and the Middle East. Surprisingly, there is a notable lack of research on coastal dune vegetation in the Great Lakes Basin, with more prominent areas of remote-sensing research in the Great Lakes involving wetland monitoring and invasive species mapping (e.g., Midwood and Chow-Fisher, 2012; Jollineau and Howarth, 2008; Tulbure, Johnston, and Auger, 2007). Nevertheless, coastal dunes remain fragile and rare ecosystems in the Great Lakes that require monitoring and investigation given their importance to both natural and human systems. Due to threats from both natural forces and human development, accurate LULC maps are required for conservation and management initiatives to ensure the long-term sustainability of coastal dune ecosystems in the Great Lakes. The Town of Saugeen Shores has cited the need for this information in their 2013 Waterfront Master Plan in order to ensure this important resource is maintained (Town of Saugeen Shores, 2013). Thus, this research project will contribute to an underdeveloped area of the academic literature by providing spatial, spectral, and temporal information of dune vegetation within the Chantry Dune system. Furthermore, the uncertainties associated with climate change, especially those relating to water temperature and lake levels, will have repercussions for shoreline and dune management in the coming years (Angel and Kunkel, 2010; Taylor, Gray, and Schiefer, 2006). Thus, the need for this research is readily apparent and will greatly benefit local governments, agencies, citizens,

and stakeholders in dune management and stewardship efforts. Finally, this research will contribute in the further refinement of the methodologies and remotely sensed datasets that are most appropriate for the study of coastal dune vegetation.

Chapter Three: Data and Methodology

3.1 - Introduction

The previous chapter provided a detailed discussion of the various image analysis approaches used to map and monitor coastal dune vegetation. This chapter outlines and provides a rationale for the data and methodology employed in this research project, including data acquisition, image preprocessing operations, and the analytical methods performed on the datasets. These included the production of NDVI images, supervised image classification, and change-detection analysis. First, the data acquisition process is outlined, followed by a discussion of the image preprocessing operations performed on the remote-sensing data. In particular, preprocessing operations consisted of data quality assurance, and geometric and radiometric correction. An explanation of the post-classification change-detection analysis of the NDVI images, and the supervised image classification, which involved the application of the maximum-likelihood algorithm to the GeoEye-1 imagery to produce a LULC map of the Chantry Dune system is then provided. The chapter concludes with a discussion on the qualitative and quantitative accuracy assessment performed after the supervised classification.

3.2 - Data Acquisition

In June 2015, two remote-sensing images covering the Chantry Dunes were purchased from eMap International, an authorized distributor of DigitalGlobe imagery. One of these images was acquired using QuickBird in 2005 with a spatial resolution of 2.44 m while the other image was recorded in 2012 by GeoEye-1 with a spatial resolution of 1.65 m (**Table 3.1**). It is important to note that although GeoEye-1 acquires imagery at a spatial resolution of 1.65 m, as per United States government regulations, GeoEye-1 data are sold at a spatial resolution of 2.0 m (DigitalGlobe, 2012a). The remote-sensing data were delivered by eMap International via file

transfer protocol with the panchromatic and multi-spectral bands in separate GeoTIFF files. The data were delivered with standard geometric corrections already performed. These corrections included the projection of the imagery to a plane using the map projection and datum (UTM WGS84). A coarse digital elevation model (DEM) was also applied to normalize for topographic relief prior to the delivery of these data (DigitalGlobe, 2014c). In order to perform further preprocessing operations and subsequent image analyses, the datasets were imported into the Environment for Visualizing Images (ENVI), version 5.2, an image-analysis software package commonly used in remote sensing.

Table 3.1: Parameters of the QuickBird and GeoEye-1 Satellites

Parameter	Spectral Band	QuickBird	GeoEye-1
Date Launched		October 2001	September 2008
Spatial resolution (m)	Panchromatic	0.61	0.41
	Multi-spectral	2.44	1.65
Spectral resolution (μm)	Panchromatic	0.45-0.90	0.450-0.900
	Blue	0.45-0.52	0.450-0.520
	Green	0.52-0.60	0.520-0.600
	Red	0.63-0.69	0.625-0.695
	Near-infrared (NIR)	0.76-0.90	0.760-0.900
Swath width (km)		16.5	15.3
Off-nadir pointing		$\pm 30^\circ$	$\pm 30^\circ$
Radiometric Resolution		11-bit	11-bit
Temporal Resolution		1-3.5 days	1-3 days
Orbital altitude (km)		450	681

(Sources: DigitalGlobe, 2014a; 2014b)

These multi-spectral datasets were used in the production of multi-temporal NDVI images; to perform supervised image classification to produce a LULC map; and perform change-detection analysis. To permit change detection, it is imperative to acquire images on anniversary dates because of sun angles, seasonal differences, and seasonal variances in plant phenology (Lillesand et al., 2008; Jensen, 2005). Accordingly, both images selected for this

research project were acquired during the month of July (**Table 3.2**). As the Chantry Dune system is small (approximately 8 ha) in area, high resolution imagery was required to accurately map and monitor the dune system. However, the relative infancy of these high-resolution sensors (QuickBird and GeoEye-1) limited the availability of data for historical dates and, thus, greatly influenced the time period studied. The selection of the 2005 to 2012 study dates was influenced by several factors, including the availability and quality of remote-sensing imagery, financial limitations, and the years 2005 and 2012 mark the thirteenth and twentieth anniversaries respectively, of the Chantry Dune Project's completion (as discussed in Chapter One).

Table 3.2: Acquisition Dates of the Remote-sensing Imagery Analyzed in this Study

Date of Acquisition	Platform	Spatial Resolution	Cloud Cover
9 July 2005	QuickBird	2.4 m	0%
28 July 2012	GeoEye-1	2.0 m	0%

3.3 - Image Preprocessing

3.3.1 - Data Quality Assurance

Before image analysis and before useful information can be extracted from remotely sensed data, the dataset must be preprocessed to ensure that the remote-sensing data are of high geometric and radiometric quality. All image preprocessing and subsequent analyses were conducted using the ENVI 5.2. Data quality assessment involved both qualitative and quantitative techniques including visual interpretation of the data (i.e., producing true- and false-colour composites), histogram analyses, and the calculation of descriptive statistics. The outcomes of data quality analyses are important as they often influence the further preprocessing operations to be performed.

3.3.2 - Geometric Correction

Image preprocessing also involved the correction of geometric and radiometric errors. Geometric correction is important to ensure that the pixels in a remote-sensing image are in their proper geographic (x, y) location; this permits the imagery and data outputs to be subsequently used in other digital environments, such as a GIS (Jensen, 2005). Depending on the image products ordered, it is common for imagery to be delivered from the image provider already corrected for geometric errors (Digital Globe, 2014a). As discussed in section 3.2, the data were delivered from the image provider with standard geometric corrections already applied.

Given that the QuickBird and GeoEye-1 datasets have different spatial resolutions, it was necessary to resample the data to permit change-detection analysis. Accordingly, the GeoEye-1 image acquired on July 28, 2012, was resampled to a spatial resolution of 2.4 m using the nearest neighbour resampling technique. In addition, to avoid erroneous change detection results, it is important that the images being compared are co-registered to within $\frac{1}{4}$ to $\frac{1}{2}$ pixel (Lillesand et al., 2008; Lu et al., 2004). Therefore, the QuickBird and GeoEye-1 images were co-registered with a root mean square (RMS) error of 0.61 m. The image data were then re-projected to the UTM Zone 17N coordinate system prior to data processing and analyses.

3.3.3 - Radiometric Correction

To convert the digital numbers (DN's) of the QuickBird and GeoEye-1 imagery into physical units of interest and to facilitate spectral analysis and image comparison, both images were calibrated to reflectance (Franklin and Giles, 1995). Remotely sensed imagery may contain radiometric errors that are caused by environmental (e.g., atmospheric scattering, haze) or sensor malfunctions (e.g., shot noise, striping, line start/stop problems; Jensen, 2005). To ensure the quality of data analyses and the extraction of accurate thematic information, it is important for

these effects to be minimized. As previously mentioned, data quality assurance of the two images used in this study did reveal atmospheric scattering and haze. To that end, it is important for this to be corrected, given that this study involves the extraction of biophysical parameters from these images and to investigate these changes over time (Jensen, 2005; Song et al., 2001). Research studies suggest that atmospheric contributions to NDVI are significant (McDonald et al., 1998) and “can amount to 50 percent or more over thin or broken vegetation cover” (Verstraete, 1994 as cited by Song et al., 2001, pg. 233). It is therefore imperative that atmospheric correction be performed in the present study to avoid erroneous NDVI values.

There are two types of radiometric correction: absolute and relative. Absolute radiometric correction requires detailed information about the local atmospheric conditions, sensor spectral profile, as well as *in-situ* data. Conversely, relative radiometric correction is used when the data required for absolute radiometric correction are not available, as was the case in this research project (Jensen, 2005; Song et al., 2001). The QuickBird and GeoEye-1 imagery were atmospherically corrected using the dark object subtraction (DOS) method. This is a common atmospheric correction technique which uses a dark object, such as a deep water body, as a calibration target. The DOS method assumes the dark object body has uniformly zero radiance in all bands, and that any non-zero radiance is attributable to atmospheric scattering (Schowengerdt, 2007; Song et al., 2001).

To improve the overall appearance of the QuickBird image and to facilitate image interpretation and analyses, a low-pass 3 x 3 spatial filter was applied and resulted in a “smoother” image (Canada Centre for Remote Sensing, 2008; Jensen, 2005). Lastly, the final preprocessing operation involved the subset of both the QuickBird and GeoEye-1 images to exclude areas outside the Chantry Dune system from further image analyses.

3.4 - Change Detection

3.4.1 - Production of Multi-temporal NDVI Images

The NDVI was calculated using the red and near-infrared (NIR) bands from each image used in the study (**Equation 3.1**). The results of these calculations were combined into a single two band dataset so that each band represented the NDVI for both the 2005 and 2012 dates. Next, the iterative self-organizing data analysis technique (ISODATA) unsupervised image classification algorithm was applied to produce 10 groupings of spectrally similar clusters. The mean NDVI value for each cluster was then used to inform subsequent image interpretation and analyses.

$$NDVI = \frac{(NIR \text{ reflectance}) - (Red \text{ reflectance})}{(NIR \text{ reflectance}) + (Red \text{ reflectance})}$$

Equation 3.1

3.4.2 - Post-Classification Comparison

Post-classification comparison was completed using the classified NDVI images to compare July 2005 with July 2012. The comparison resulted in a 10 x 10 matrix whereby the number of rows and columns was based on the number of spectrally similar clusters grouped by the ISODATA image classification algorithm. The columns represented the NDVI clusters from 2005 (initial state) while the rows represented the NDVI clusters from 2012 (final state). For the comparison, a classified image was created so that each pixel represented a “from-to” change in the NDVI value. Next, visual interpretation of the matrices was performed to identify the different changes in NDVI values and produce a legend (i.e., increase in NDVI value, no change in NDVI value, and decrease in NDVI value). Finally, to identify the spatial pattern of NDVI change in the Chantry Dunes over the respective dates, a colour scheme was applied to corresponding pixels in the classified image. The change detection methods outlined above were used by Leahy et al. (2005) to map and monitor NDVI change in shoreline wetlands at Long Point, Ontario. The

authors concluded that post-classification comparison could be used to identify and analyze spatio-temporal patterns of NDVI change. Therefore, the approach was adopted in this current study.

3.5 - Supervised Image Classification

3.5.1 - Selection of an Appropriate Land-use/Land-cover Classification Scheme

The Ecological Land Classification (ELC) system for southern Ontario was developed in order to standardize and provide a comprehensive framework for the identification, classification, and inventory of ecological land units present in southern Ontario. The ELC was selected for this study due to its increasing prominence in ecosystem management and ecological planning in Ontario (Jollineau and Howarth, 2008; Lee et al. 1998). Moreover, the use of a standard classification system, such as the ELC, provides a baseline dataset to inform possible future research and mapping activities at the Chantry Dunes. The classes used in this study and their descriptions are listed in **Table 3.3**.

Table 3.3: The Ecological Land Classification (ELC) Scheme Used in this Research Project

Community Class	Community Series	Description
Beach / Bar	Open Beach / Sand	Exposed sands formed by current or historical shoreline or aeolian processes. Subjected to active shoreline processes; tree and shrub cover $\leq 25\%$
Water	Shallow Water	Water up to 2 metres in depth; emergent vegetation may be present but not dominant; no trees or shrub cover
Water	Open Water	Water > 2 metres in depth; no macrophyte vegetation, trees or shrub cover
Sand Dune	Treed Sand Dune	Relatively stable sand; $25\% \leq$ tree cover $\leq 60\%$
Sand Dune	Shrub Sand Dune	Sand is more stable, less disturbed; tree cover $\leq 25\%$, shrub cover $> 25\%$
Built-Up Area Impervious		Areas with buildings, pavement, and other anthropogenic features

(Source: Ontario Ministry of Natural Resources, 2008; Lee et al., 1998).

3.5.2 - Selection of Calibration and Validation Sites

The selection of calibration and validation sites for use in the supervised classification procedure was based on fieldwork conducted at the Chantry Dunes during July 2015. The dominant land-use/land-cover classes as per the ELC were identified and documented during the field campaign¹. A digital camera was used to photograph locations and appearances of some calibration sites. Global positioning system (GPS) data were also acquired for some calibration sites using a Trimble GeoXT hand-held GPS unit. Lastly, aerial photographs of the Chantry Dune system acquired from the 2010 Southwestern Ontario Orthophotography Project (SWOOP), and personal knowledge of the study area were used to inform and select calibration and validation sites for image classification.

The spectral characteristics and response patterns of calibration sites are used to generate statistics required to define classifier decision rules and are used by the algorithm to classify the remaining pixels of the image. The calibration-site data were selected and dispersed throughout the image to best capture the spectral variability of each land-use/land-cover type present in the image scene. A minimum of $10n$ to $100n$ calibration sites, where n is the number of bands used in the classification, were selected to represent each land-use/land-cover type identified in **Table 3.5**. This rule is commonly used in remote sensing because “estimates of the mean vectors and covariance matrices improve as the number of pixels in the training sets increase” (Lillesand et al., 2008, pg. 559). In short, the more calibration sites, the better the statistical representation of each information class. A summary of the number of calibration sites used for each land-use/land-cover type is listed in **Table 3.6**.

¹ It is important to note that fieldwork was restricted to public beach accesses and public property to prevent disturbance to the dune system.

Table 3.4: The Number of Calibration Pixels per Information Class

Information Class	Number of Calibration Pixels
Open Beach / Sand	1,541
Shallow Water	1,719
Open Water	1,872
Treed Sand Dune	2,064
Shrub Sand Dune	1,342
Built-up Area Impervious	754

3.5.3 - Spectral Separability

After the calibration and validation sites were selected, the spectral separability between all spectral class pairs was calculated to determine which bands to use in the classification and possible areas of classifier confusion. When performing supervised image classification, it is important to select calibration and validation sites that are spectrally separable in order to avoid classifier confusion, which can lead to erroneous classification results (Jensen, 2005; Shanmugam et al., 2003; Congalton, 1991). There are several quantitative measures that can provide useful information about the spectral separability between different land-use/land-cover type pairs. Two commonly used measures of spectral separability include transformed divergence (TD) and Jeffries-Matusita (J-M) distance. In these measurements, the higher values represent larger statistical separability between class pairs (Jensen, 2005). For example, a TD or J-M value of 2.00 represents a high spectral separability between a pair of information classes. In the current study, the TD and J-M measures of spectral separability (see Chapter Four) were used to inform which bands to use in the image classification, and refine calibration and validation sites to better capture the spectral variance of the respective information classes to increase the accuracy of the classification result.

3.5.4 - The Maximum-Likelihood Classification Algorithm

The use of a hard classifier was chosen as the most appropriate means of classifying the GeoEye-1 imagery due to the high spatial resolution of the data and the goals and objectives of this research project. The maximum-likelihood classification algorithm is useful as it incorporates the mean and covariance values of training classes to construct equiprobability contour regions. Unknown pixels that fall into these decision regions are classified to that specific class while overlapping pixels or those residing outside decision regions are labelled ‘unclassified’. However, in these contexts the bias parameter may be used by the analyst to provide weighting as to the probability of occurrence for each of the information classes (Lillesand et al., 2008; Jensen, 2005). In this study, the maximum-likelihood classification algorithm was applied to the blue, green, red, and NIR bands of the GeoEye-1 data acquired on July 28, 2012. Although there is a tendency for the blue band to be susceptible to Rayleigh scatter and atmospheric interference (Lillesand et al., 2008), it was included in the image classification as its inclusion improved the accuracy of the final classification result.

3.5.5 - Classification Accuracy Assessment

Accuracy assessment is a critical aspect of the classification procedure as it not only informs the image analyst about the level of correctness, but provides the end user with a level of confidence in their use of the map product. Additionally, the results can also be used to identify areas for improvement, which can be implemented in subsequent classification initiatives (Foody, 2008; Lillesand et al., 2008; Congalton, 1991). The accuracy assessment of the final classification result involved both qualitative and quantitative techniques. Qualitative assessment included a visual interpretation of the classification result based on personal knowledge of the study area, which was reinforced through visits to the study site in July 2015. In addition, the production of

a line graph depicting the spectral separability of each land-use/land-cover class was also used to qualitatively assess the classification result.

The quantitative assessment involved the calculation of the quantitative measures to assess classification results, including the kappa coefficient of agreement (or KHAT), overall accuracy, user's accuracy, and producer's accuracy. Analysis of the confusion matrix, which used validation sites from field data, was also performed to assess the accuracy of the classification results (Congalton and Green, 2009).

After an acceptable level of accuracy was achieved (i.e., 85% or higher), a post-classification filter was applied to the final classification result to improve the overall aesthetics of the LULC map. This is a common procedure performed after image classification to remove isolated pixels and improve the overall aesthetics of the land-use/land-cover map. In particular, a mode filter (3 x 3-pixel) was applied to the final classification result. As the 3 x 3 moving window proceeds through the classification result, the majority class is determined; if the window's centre pixel does not belong to the majority class, it is changed to the majority class. Conversely, if there is no majority class present within the window, the identity of the centre pixel remains unchanged (Lillesand et al., 2008). In complex heterogeneous areas, such as dune environments, smaller sand dune features can be removed by spatial filters and thus result in the loss of important LULC information. Accordingly, the 3 x 3-pixel mode filter was applied only to certain classes, including open water, shallow water, and impervious built-up areas.

3.6 - Chapter Summary

This chapter described and justified the data and methodological approaches used to meet the goal and objectives of this research project. The chapter began with a discussion on the

acquisition of the QuickBird and GeoEye-1 remote-sensing imagery and the image preprocessing operations, including geometric and radiometric corrections that were applied before image analysis. This was followed with an explanation of the change-detection analysis which involved the production of multi-temporal NDVI images and the post-classification change comparison of NDVI clusters to determine the spatial and temporal patterns of change in vegetation cover. Next, the methodology involved in the supervised image classification was highlighted. This process included the selection of the ELC scheme, the selection of calibration and validation sites, calculation of the spectral separability among LULC classes, and the application of the maximum-likelihood classification algorithm to the GeoEye-1 imagery. The chapter concluded with a discussion of the classification accuracy assessment performed on the classification result which included the use of both qualitative and quantitative techniques to ensure an acceptable level of accuracy was achieved. The following chapter will present a detailed analysis and discussion of the results obtained.

Chapter Four: Results and Discussion

4.1 - Introduction

This chapter presents the results and discussion of the analytical methods performed on the QuickBird and GeoEye-1 remote-sensing datasets as outlined in Chapter Three. The chapter begins with a discussion of the results from the image preprocessing operations. Next, the results from the production of the multi-temporal NDVI images for 2005 and 2012 are presented. This is followed by the results of the post-classification comparison of the classified NDVI images to reveal changes in NDVI values within the Chantry Dune system between July 2005 and July 2012. Next, the accuracy assessment results of the supervised image classification, which involved the application of the maximum-likelihood classification algorithm to the GeoEye-1 dataset, are presented, discussed, and analyzed. The chapter concludes with a discussion on the limitations of the present research project.

4.2 - Image Preprocessing

The production and subsequent visual analysis of true- and false-colour composites revealed no obvious data anomalies, such as shot noise, banding, or striping. There did, however, appear to be haze in both the QuickBird and GeoEye-1 images although it was more prevalent in the former; details regarding how this was addressed were discussed in Chapter Three. In addition, the northwest portion of the QuickBird image was impacted due to the wave conditions on Lake Huron at the time that the data were collected. This area was included in the mask applied (see below) and thus was not involved in any further image analyses. An examination of the descriptive statistics and histograms (**Figures 4.1** and **4.2**) for both the QuickBird (**Table 4.1**) and GeoEye-1 (**Table 4.2**) imagery revealed values that made sense based on personal knowledge of the study area and the reflectance characteristics of the different Earth-surface

features present in the imagery. For example, the image scene contained significant areas of vegetation and water, which explained the low mean and standard deviation for the blue band (Band 1) and the high NIR mean (Band 4). In addition, given the types of vegetation present (e.g., mixed forest, agricultural crops) combined with the time of year the images were acquired (July), the high NIR mean and standard deviation also make sense. This also explained the lower mean for the red band (Band 3) in both images. Further detail regarding the descriptive statistics and histograms were included in **Appendices B** and **C**.

Table 4.1: Descriptive Statistics for Bands 1-4 of QuickBird Data (acquired July 9, 2005)

Band Number	Minimum	Maximum	Mean*	Standard Deviation*
1 (Blue)	1	2047	229.9	75.7
2 (Green)	1	2047	320.8	135.8
3 (Red)	1	2047	176.2	125.0
4 (NIR)	1	2047	671.4	441.0

***NOTE: These values have been rounded to the nearest tenth.**

Table 4.2: Descriptive Statistics for Bands 1-4 of GeoEye-1 Data (acquired July 28, 2012)

Band Number	Minimum	Maximum	Mean*	Standard Deviation*
1 (Blue)	293	2047	377.8	68.4
2 (Green)	157	2047	272.4	68.1
3 (Red)	60	2047	161.1	97.3
4 (NIR)	52	2047	755.8	389.1

***NOTE: These values have been rounded to the nearest tenth.**

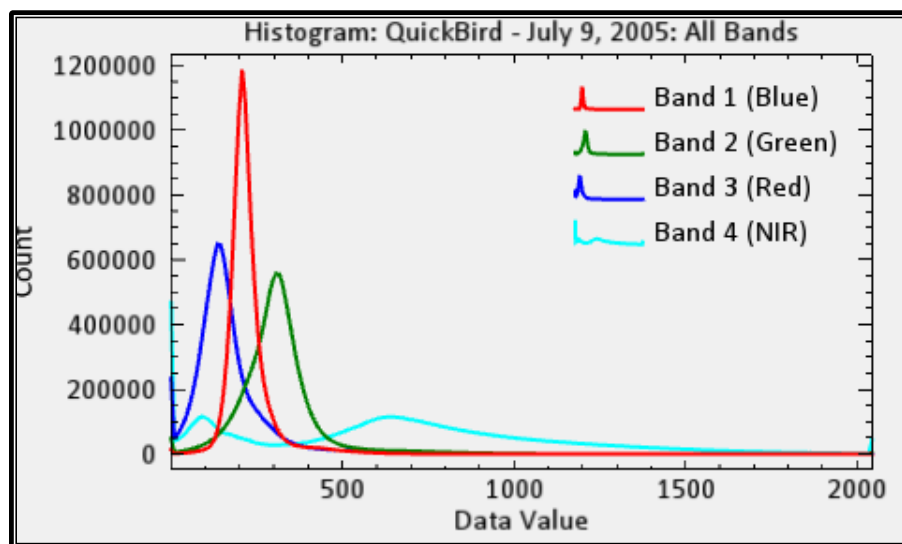


Figure 4.1: Histogram of the QuickBird imagery acquired on July 9, 2005.

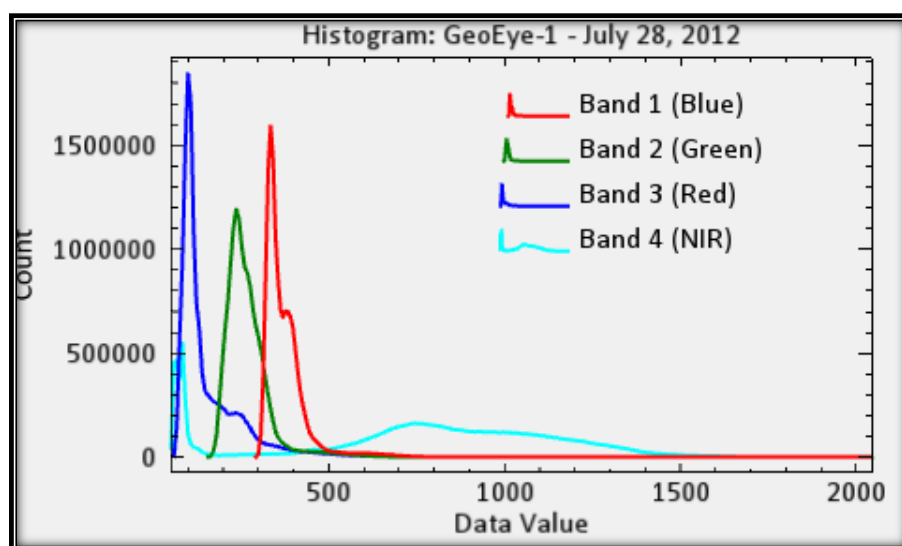


Figure 4.2: Histogram of the GeoEye-1 imagery acquired on July 28, 2012.

4.3 - Change Detection

4.3.1- Production of Multi-temporal NDVI Images

The multi-temporal NDVI images of the Chantry Dune system in July 2005 and July 2012 are presented in **Figure 4.3** and **Figure 4.4**. Final map products displaying these NDVI images were included in **Appendices D** and **E**. The descriptive statistics for these NDVI images are listed in **Table 4.3** and **Table 4.4**. These statistics were consistent with what one would expect given the different Earth-surface features, including large water bodies, built-up areas, and lush, healthy vegetation, that were present in both the QuickBird and GeoEye-1 imagery. The histograms shown in **Figure 4.5** and **Figure 4.6** provided further details of the NDVI values and Earth-surface features present in the image scenes. When comparing the histograms, there were noticeable differences between the QuickBird and GeoEye-1 NDVI images. One difference was the percentage of image pixels that had NDVI values less than zero. Approximately 14% of image pixels in the 2005 QuickBird NDVI image (**Figure 4.3**) had NDVI values less than zero. In contrast, the 2012 GeoEye-1 NDVI image (**Figure 4.4**) had approximately 43% of image pixels have NDVI values less than zero. Given the presence of a large water body (i.e., Lake Huron) in the image scene, one would expect that a considerable number of pixels would have NDVI values less than zero.



Figure 4.3 (left): NDVI image of the Chantry Dune system in 2005. This image was generated from QuickBird imagery acquired on 9 July 2005.

Figure 4.4 (right): NDVI image of the Chantry Dune system in 2012. This image was generated from GeoEye-1 imagery acquired on 28 July 2012.

Table 4.3: Descriptive Statistics for the Normalized Difference Vegetation Index (NDVI) Image Derived from QuickBird Data (Southampton, Ontario, July 9, 2005)

Minimum	Maximum	Mean	Standard Deviation
-0.8999	0.977118	0.038607	0.202408

Table 4.4: Descriptive Statistics for the Normalized Difference Vegetation Index (NDVI) Image Derived from GeoEye-1 Data (Southampton, Ontario, July 28, 2012)

Minimum	Maximum	Mean	Standard Deviation
-0.74183	0.947986	0.027579	0.452012

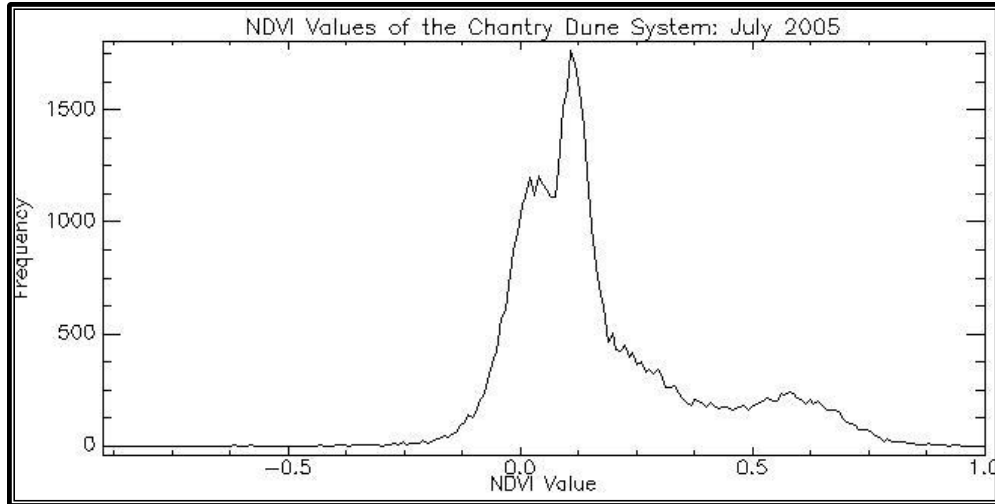


Figure 4.5: Histogram of the NDVI image derived from bands 3 (red) and 4 (NIR) of QuickBird data acquired on July 9, 2005.

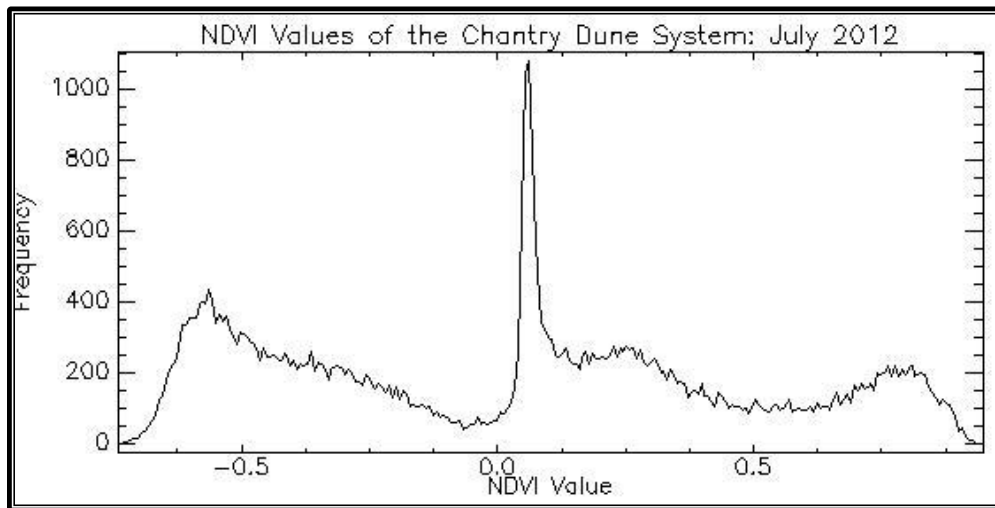


Figure 4.6: Histogram of the NDVI image derived from bands 3 (red) and 4 (NIR) of GeoEye-1 data acquired on July 28, 2012.

Wave conditions, water depth, water column attenuation, and turbidity of the water at the time of data acquisition (**Figure 4.3**) can influence how electromagnetic energy is absorbed and reflected (Cho, Mishra, and Wood, 2012; Lillesand et al., 2008; Spitzer and Dirks, 1987). Consequently, this can impact the calculation of NDVI values. In the QuickBird image, the wave conditions were noticeably choppy and whitecaps were evident. The windy and wavy conditions

on July 9, 2005 were further corroborated from historical weather data (Environment Canada, 2015b). Although there is limited historical hourly weather data available for Southampton, Ontario during the time periods under investigation, the nearest weather station located in Wiarton, Ontario recorded wind speeds of 15 to 20 km/h in the hours prior to and during the acquisition of the QuickBird data. These windy conditions were also recorded in the days before the remote-sensing data acquisition on July 9, 2005, which would have further stirred sediment and influenced the overall turbidity of the water (Environment Canada, 2015b).

Examination of the QuickBird histogram also revealed that approximately 11% of pixels have NDVI values greater than 0.5, representing lush, dense vegetation. In the QuickBird NDVI image, the dense vegetation was generally found to the west of the Front Street parking lot, at a few locations throughout the dune system, and in the surrounding residential areas (**Figure 4.7**). Approximately, 75% of the pixels had NDVI values greater than zero, but less than 0.5. This was expected, given that sparse vegetation, such as dune vegetation and shrubs, having typically moderate NDVI values ranging from approximately 0.2 to 0.5 (Holben, 1986).

In comparison, the GeoEye-1 NDVI image had approximately 18% of pixels with NDVI values greater than 0.5 while approximately 39% of pixels have NDVI index values greater than zero, but less than 0.5. Similar to the QuickBird image, a majority of the dense vegetation (i.e., NDVI values greater than 0.5) could be found in the same locations specified above. These areas also covered a greater proportion of the dune system than in 2005. In the 2012 GeoEye-1 NDVI image (**Figure 4.4**), there was noticeably more dense vegetation in the area to the west of the Front Street parking lot, and the dunes to the west of Harmer Street than in 2005.

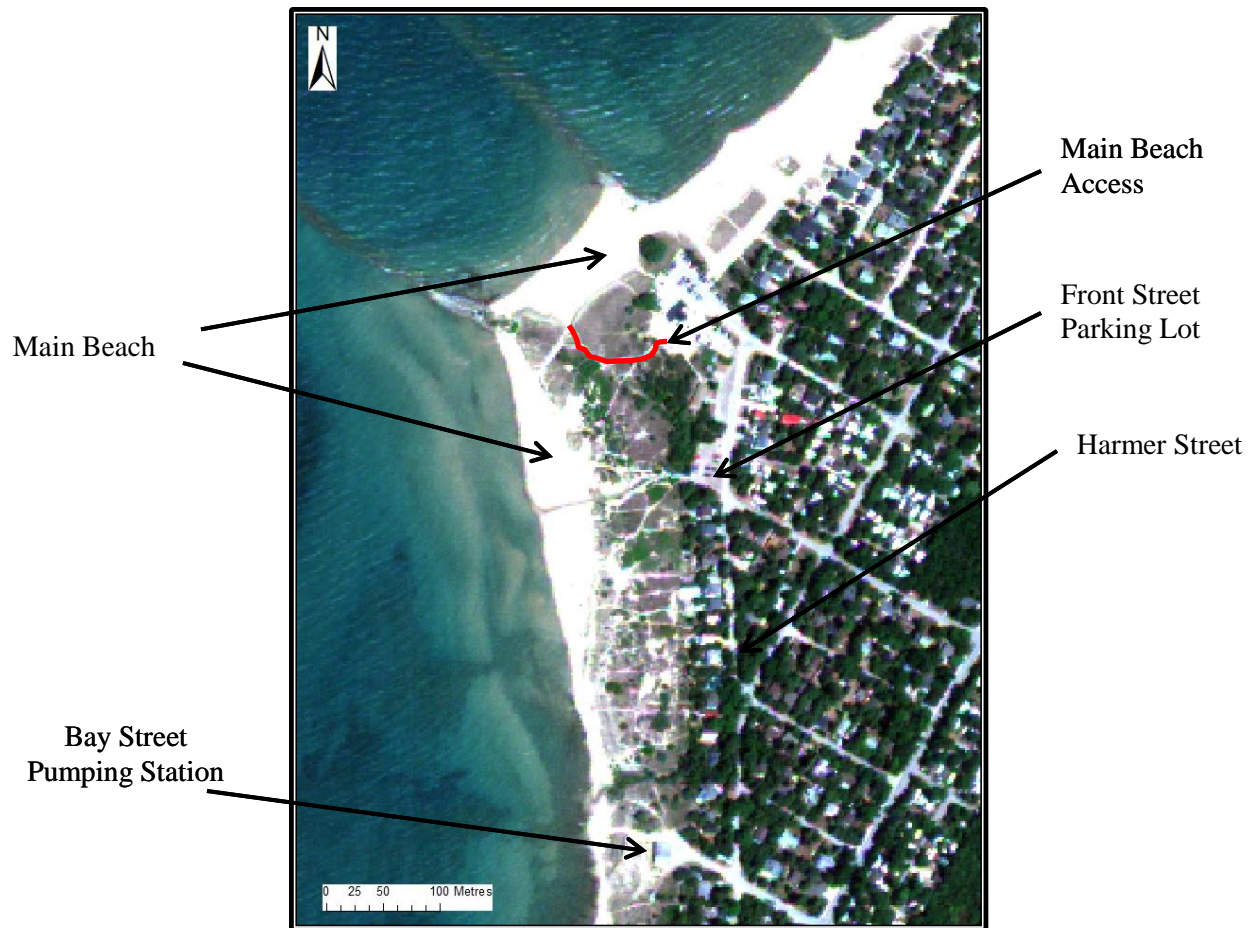


Figure 4.7: True-colour composite GeoEye-1 image of the Chantry Dune system (2012) highlighting some important locations referenced in-text. The red line highlights the main beach access pathway.

The slightly higher percentage of pixels with NDVI values greater than 0.5 might be attributable to further vegetation growth within the dune system (**Figure 4.4**); however, this could also be influenced by other factors, including the later acquisition date (July 28, 2012) of the GeoEye-1 imagery and associated phenological differences. For example, two prominent vegetation species in the Chantry Dune system, American Beach Grass (*Ammophila brevigulata*) and Pitcher's Thistle (*Cirsium pitcheri*), bloom in mid-summer and prefer full sun and dry conditions (Clark and Peach, 2010). A review of available weather data revealed that in the month leading up to the image acquisition date of the QuickBird data, the average median

temperature was 19.4°C, with 63.9 mm of total precipitation (**Figure 4.8**). In 2012, the month prior to image acquisition had an average median temperature of 20.5°C and a total of 53 mm of precipitation (**Figure 4.9**) (Environment Canada, 2015b; Environment Canada, 2015c). Thus, the overall weather conditions in 2012 were more favourable for several vegetation species within the dune system.

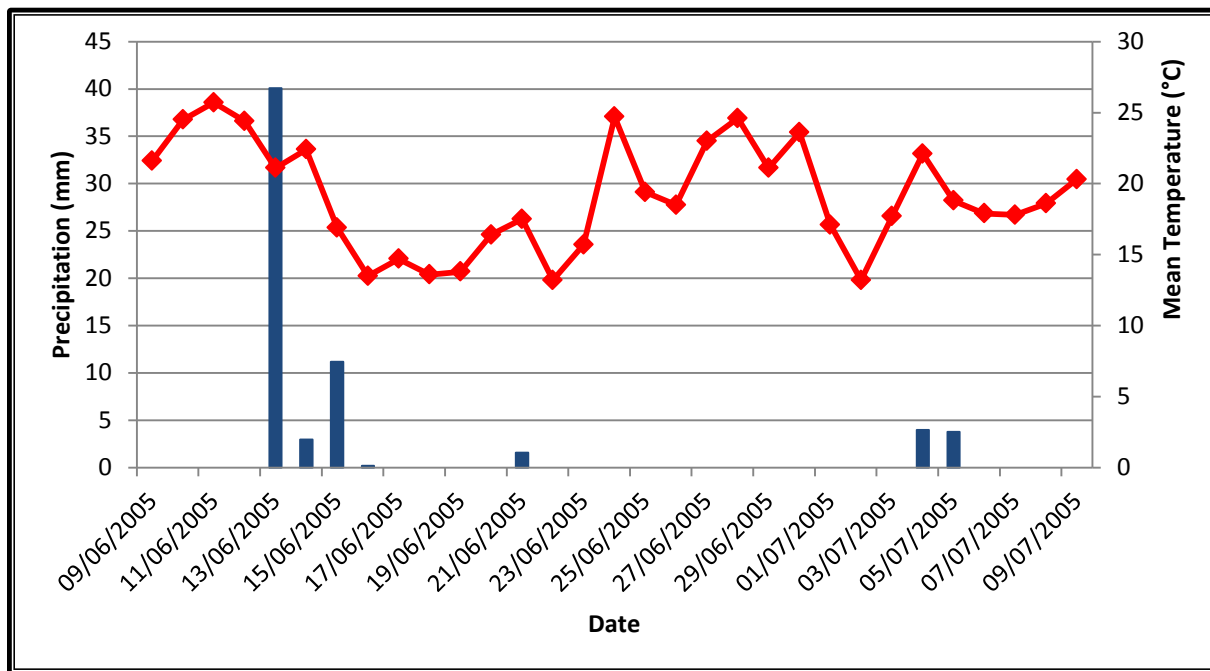


Figure 4.8: Climate graph for Wiarton, Ontario from June 9, 2005 to July 9, 2005. (Source: Environment Canada, 2015b).

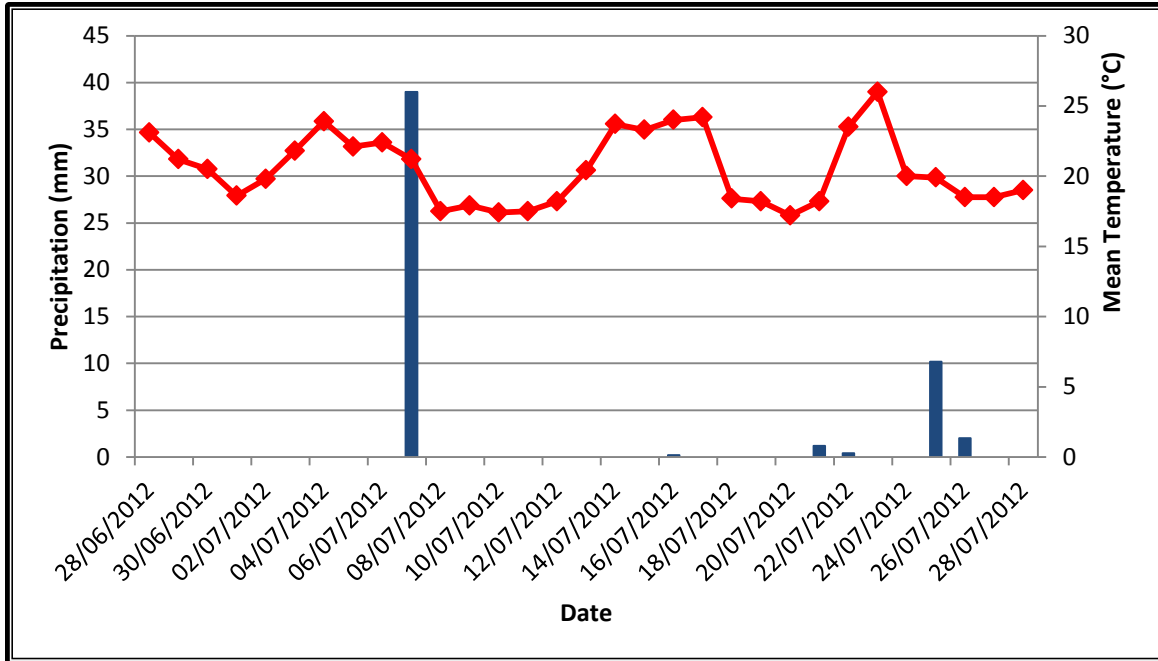


Figure 4.9: Climate graph for Wiarton, Ontario from June 28, 2012 to July 28, 2012 (Source: Environment Canada, 2015c).

A visual examination of the two NDVI images in **Figures 4.3** and **4.4** also revealed noticeable changes in dune vegetation extent between 2005 and 2012. In the 2012 NDVI image there was a notable increase in the extent of dune vegetation within the Chantry Dune system compared to 2005. Specifically, locations A, B, C, D, and E (**Figure 4.10**) were examples of areas that had witnessed increased growth in dune vegetation since 2005. The observed dune vegetation growth in some locations had impacted the trails, pathways, and sidewalks within the Chantry Dune system. While pathways through the dune system were visible in both the 2005 and 2012 NDVI images, there were some instances where dune vegetation had overgrown onto trails and pathways, consequently narrowing these access points. For example, one of the main pathways through the dune system (demarcated by the red line in **Figure 4.7**) was one such

pathway that had been narrowed due to dune vegetation growth. The narrowing of this pathway was also evident from field site observations in July 2015, as shown in **Figure 4.11**.

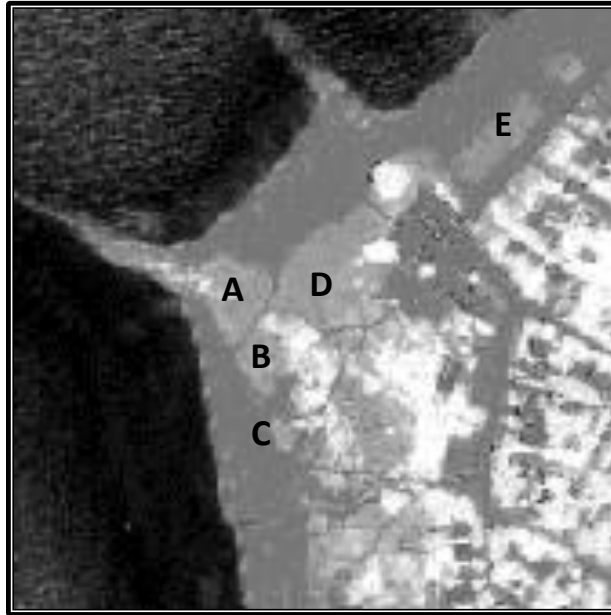


Figure 4.10: Enlarged NDVI image of the Chantry Dune system in 2012. The letters represent some sections of the dune system that have witnessed dune vegetation growth since 2005.



Figure 4.11: One of the main pathways through the Chantry Dune system highlighting the narrowing of beach access points due to the overgrowth of dune vegetation. (Source: B. Hague, 2015).

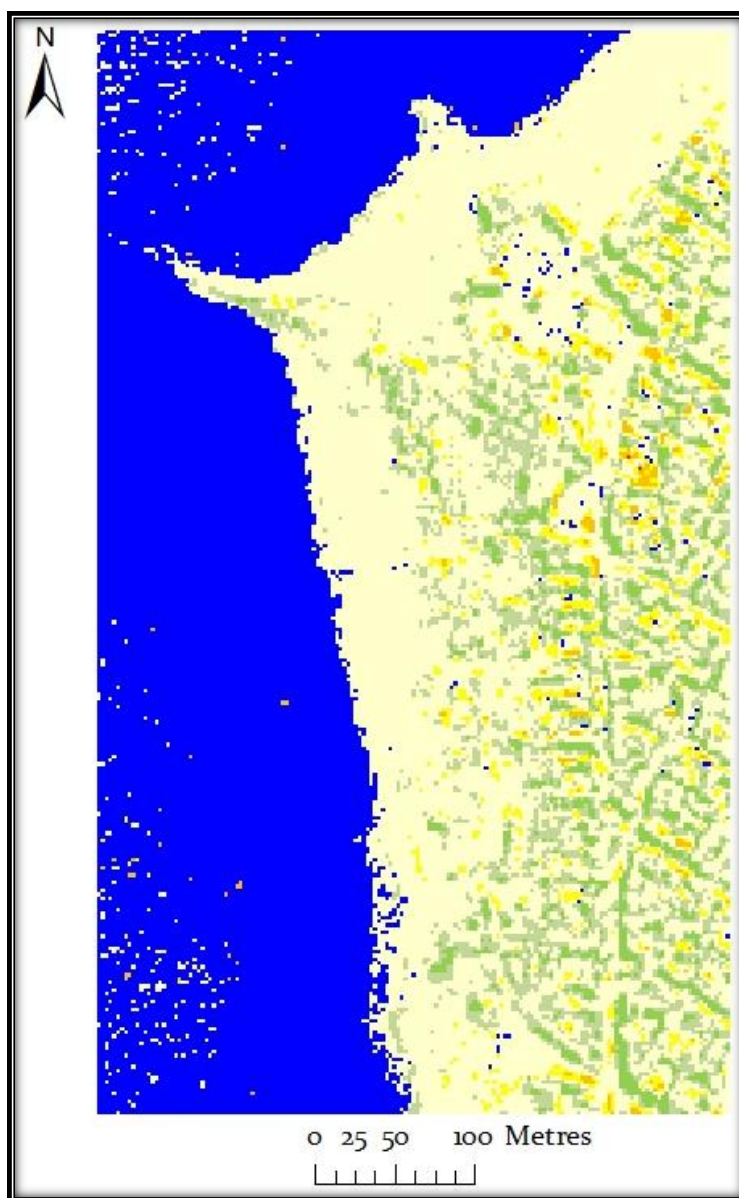
4.3.2 Post-Classification Comparison

Results of the post-classification comparison of the classified NDVI images comparing July 2005 with July 2012 are presented in **Figure 4.12**. A detailed tabulation of NDVI change between the two classified images is also presented in **Table 4.6**. The mean position of the NDVI values for July 2005 (i.e., initial state) is listed in the columns while the mean position of the NDVI values for July 2012 (i.e., final state) is listed in the rows. Thus, each cell in the table represents the number of pixels that changed from the initial NDVI value in 2005 to a subsequent NDVI value in 2012. The NDVI change represented by each cell was determined by comparing the difference between the NDVI cluster mean values for the 2005 and 2012 dates. A coloured legend, similar to the one used by Leahy et al. (2005), was then assigned based on the NDVI change (e.g., increase or decrease) and the magnitude of such change. The eight legend categories used are described in **Table 4.5**.

Table 4.5: Legend Categories Used in the Post-Classification Comparison

Colour	Description of Change
Blue	Pixels with NDVI values less than zero on both dates or pixels known to be water
Dark Green	Pixels with NDVI values that increased from 2005 to 2012 by 1.0 or greater
Green	Pixels with NDVI values that increased from 2005 to 2012 by at least 0.5 but less than 1.0
Light Green	Pixels with NDVI values that increased from 2005 to 2012 by at least 0.2 but less than 0.5
Pale Canary	Pixels with NDVI values that remained unchanged (± 0.2) from 2005 to 2012
Yellow	Pixels with NDVI values that decreased from 2005 to 2012 by at least 0.2 but less than 0.5
Orange	Pixels with NDVI values that decreased from 2005 to 2012 by at least 0.5 but less than 1.0
Red	Pixels with NDVI values that decreased from 2005 to 2012 by 1.0 or greater.

In **Figure 4.12**, the dune system was primarily dominated by pale canary and green pixels indicating that NDVI values remained relatively unchanged or increased slightly from 2005-2012. The majority of pixels that represented an increase in NDVI values were located to the west of the Front Street Parking lot and along Harmer Street. It is important to note there were no extreme changes (i.e., increases or decreases greater than 1.0) in NDVI values from 2005 to 2012. A final map product displaying the results of the post-classification comparison is found in **Appendix F**.



Legend	
■ Water - (< 0.0 NDVI both dates)	■ Little or no NDVI change (± 0.2)
■ Increase in NDVI (by at least 1.0)	■ Decrease in NDVI by 0.2 to less than 0.5
■ Increase in NDVI by 0.5 to less than 1.0	■ Decrease in NDVI by 0.50 to less than 1.0
■ Increase in NDVI by 0.2 to less than 0.5	■ Decrease in NDVI by at least 1.0

Figure 4.12: Post-classification change comparison of NDVI clusters from the July 2005 QuickBird and the July 2012 GeoEye-1 image.

Table 4.6: Mean Positions for NDVI Clusters: July 2005 and July 2012

Initial State: July 2005												
Final State: July 2012	Class Means		-0.09975	-0.00118	0.057768	0.107836	0.146907	0.193294	0.250107	0.327285	0.463364	0.643175
			Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
	-0.56118	Class 1	956	4430	2974	871	164	11	3	0	0	0
	-0.38814	Class 2	427	1274	1504	1312	764	126	7	2	1	2
	-0.25111	Class 3	114	387	549	806	952	257	14	2	0	5
	-0.13968	Class 4	76	214	259	329	497	158	11	6	6	17
	-0.01887	Class 5	60	194	200	153	178	70	26	36	29	47
	0.072333	Class 6	220	446	607	2695	1363	506	313	236	181	235
	0.176044	Class 7	107	207	248	612	611	540	510	403	257	277
	0.291417	Class 8	98	95	171	524	600	590	915	811	497	411
	0.473519	Class 9	120	113	167	272	315	369	510	707	799	681
	0.76152	Class 10	252	232	230	273	259	327	430	726	1469	2678

4.3.3 - Change Detection Discussion

The observed increase in dune vegetation within the Chantry Dunes was likely influenced by a variety of factors. In terms of environmental factors, lake water levels can influence the growth of sand dunes and dune vegetation (Wilcox et al., 2007). As previously discussed in Chapter One, during periods of high water levels, less of the beach area is exposed to wind erosion, while during periods of low water levels a larger area of the beach is exposed. The latter scenario tends to result in the growth of dunes and vegetation succession in the direction of the lake (Lake Huron Centre for Coastal Conservation, 2015; Peach, 2003). It is important to highlight that the time period under investigation (2005-2012) was during the lengthiest period on record of low water levels on the Great Lakes (The Canadian Hydrographic Service, 2014). Therefore, the low water levels from 2005-2012 provided favourable environmental conditions that facilitated the growth of sand dunes and dune vegetation towards Lake Huron. Other factors influencing and contributing to the increased vegetation growth within the Chantry Dune system include management practices, such as the continued education and awareness of the importance of dune system among local residents and tourists (Town of Saugeen Shores, 2013).

While the increased dune vegetation growth within the Chantry Dunes is positive in terms of stewardship and conservation efforts, dune overgrowth in some areas of the Chantry Dune system is a concern for some local residents, especially those who own property that abuts onto the dune system (Town of Saugeen Shores, 2013; Sutherland, 2011). Some of these residents, represented by the Southampton Residents Association (SRA), have complained to the town that the growing height of the dunes and vegetation is impacting their scenic views of Lake Huron and Chantry Island, and depreciating property values. Unfortunately, in some instances,

there have been reports of residents taking it upon themselves to manicure and remove dune grass (Town of Saugeen Shores, 2013).

In addition, there have also been concerns from residents that expanding dune vegetation has resulted in a loss of beach area for beachgoers (Town of Saugeen Shores, 2015a).

Specifically, sections B and C of the dune system, as highlighted in **Figure 4.10**, are notable areas where dune vegetation has decreased the size of the beach. The field study conducted in July 2015 also revealed these sections of the dune system have continued to grow considerably since 2012 and now extend almost to the water's edge in some areas (**Figure 4.11**). This has provided complications for some beachgoers who now resort to wading into the water or transverse through the dune vegetation to access the beach thereby trampling and further impacting the vegetation.



Figure 4.13: Dune vegetation growth in some areas has made accessing the beach difficult. (Source: B. Hague, 2015).

In response to these concerns, the Town of Saugeen Shores has collaborated with the Ministry of Natural Resources (MNR) and the Lake Huron Centre for Coastal Conservation to seek possible solutions. With respect to the dune height along Harmer Street, permanent snow fencing was installed in 2014 and dune grass was planted in an attempt to curtail dune growth (Town of Saugeen Shores, 2015b; Town of Saugeen Shores, 2011). Reducing the height of the dunes by other means (e.g., sand removal) had been called a “massive undertaking” by one town official and would require approval from the MNR and the Saugeen Valley Conservation Authority (Sutherland, 2011). The town had also recently developed a draft Beach Maintenance Plan (Town of Saugeen Shores, 2015a; Town of Saugeen Shores, 2015c) in consultation with stakeholders, including the Southampton Residents Association, which outlined the management and level of services (i.e., beach raking, snow fence installation, etc.) conducted at the town’s beaches. The Beach Maintenance Plan does highlight the impact of lower water levels on the growth of dune vegetation lake-ward, but does not provide further specification and detail as to how this can be managed. The plan notes that “wave action will always maintain a beach of varying width” and that “to accommodate all users of the waterfront, the municipality will have to play a role to ensure that beach space is optimized” (Town of Saugeen Shores, 2015a, pg. 4). The migration of dune vegetation towards Lake Huron is likely to be a continuing issue in the coming years given the uncertainties surrounding climate change and their impact on water levels, although some models suggest a decrease in water levels (Angel and Kunkel, 2010).

Overall, the NDVI and change-detection results indicate that current dune management initiatives, including increased education and local awareness, in combination with environmental factors such as low water levels and favourable mean temperature and precipitation totals, have facilitated the observed growth of dune vegetation. That being said,

there is a concern from some residents that the overgrowth of dune vegetation and sand dunes in some areas is beginning to impact the overall appearance of the public beaches. Accordingly, this highlights the tension between managing the sustainability of the ecosystem and the aesthetics of the beach; this is an issue that requires ongoing attention and monitoring moving forward considering the beach is a prominent tourist attraction for Southampton and the Town of Saugeen Shores.

4.4 - Supervised Image Classification

4.4.1 - Spectral Separability

The qualitative assessment of the spectral separability between LULC classes revealed good spectral separability between most of the LULC classes present within the Chantry Dunes system. Among the six LULC classes, the spectral signatures were most similar within the blue portion of the spectrum while the greatest difference in spectral signatures occurred in the NIR regions of the spectrum (**Figure 4.14**). This was not unexpected, given the mixture of vegetation, water, and urban features present in the image scene. There were however, some similarities in spectral signatures among a few classes. In particular, the spectral signatures of the “Built-Up Area Impervious” and “Shrub Sand Dune” classes were spectrally similar throughout the blue, green, and red portions of the spectrum with the greatest separability occurring in the NIR portion of the electromagnetic spectrum due to the increase in spectral response of the “Shrub Sand Dune” class. This is a result of the increased reflection of NIR energy among the shrub vegetation; a pattern consistent with the spectral signature of vegetation (Xie et al., 2008).

In the quantitative assessment of spectral separability, the Transformed Divergence (TD) and Jeffries-Matusita (J-M) distances were calculated for the calibration-site data as displayed in **Table 4.7**. As discussed in Chapter Three, these values ranged from 0-2, where zero represented

poor separability and two represented excellent separability. All spectral pairs had good spectral separability with TM and J-M distances greater than 1.83. The most separable pairs were: “Open Water” and “Shrub Sand Dune”; “Open Beach” and “Treed Sand Dune”; and “Open Beach” and “Open Water.” In contrast, “Built-Up Area Impervious” and “Shrub Sand Dune” were the least separable land-use/land-cover pairs with TM and J-M distances of 1.83 and 1.97, respectively.

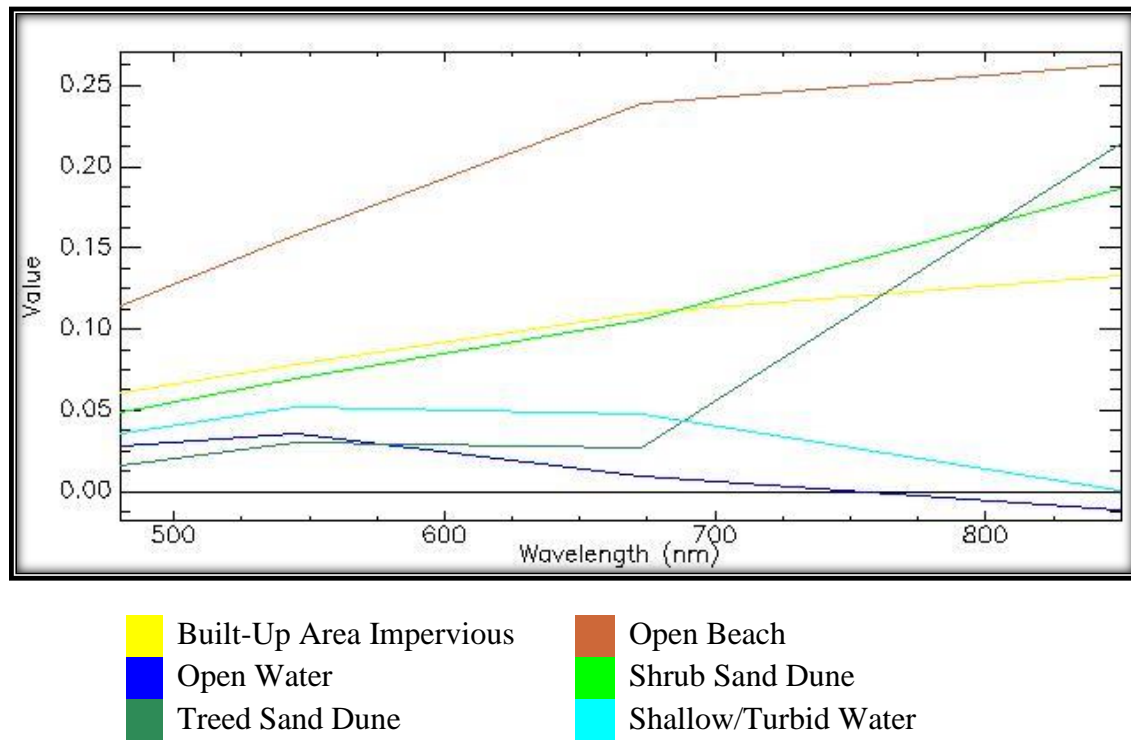


Figure 4.14: Spectral response curves of the land-use/land-cover classes in the Chantry Dune system.

4.4.2 - Maximum-Likelihood Classification Algorithm

The final classification result is presented in **Figure 4.15** and a summary of the class statistics is provided in **Table 4.8**. A total of six information classes were mapped. Not surprisingly, the water classes (“Open Water” and “Shallow/Turbid Water”) were the largest information classes. The sand dune information classes (“Shrub Sand Dune” and “Treed Sand Dune”) each accounted for approximately 15% of the study area. The smallest information class was “Open Beach” with

an area of approximately 23,000 m². A final version of the classification map is presented in **Appendix G**.

4.4.3 - Accuracy Assessment: Maximum-Likelihood Classification Algorithm

The classification accuracy assessment consisted of both qualitative and quantitative analyses of the results. Qualitative examination of the classification result indicated that the classification was successful overall. The quantitative assessment involved the computation of an error matrix based on validation sites selected from field data (**Table 4.9**). In addition, producer's and user's accuracies as well as errors of omission and commission were also calculated (**Table 4.10**).

Based on the qualitative assessment of the land-use/land-cover map (**Figure 4.15**), and the results in **Tables 4.7, 4.8, and 4.9**, it is apparent the LULC classes have been accurately mapped. However, a visual examination of the classification result reveals a few areas throughout the dune system which proved challenging for the classifier. For example, some pixels occupying the transition zone between the "Shrub Sand Dune" and "Open Beach" information classes have been mistakenly classified as "Built-Up Area Impervious." In addition, some areas that should be classified as "Open Beach" were instead classified as "Built-Up Area Impervious." The effects of these can be minimized through the application of a mode filter to produce a final information output product.

Table 4.7: Spectral Separability Measures for Calibration Data

Class	Built-Up Area Impervious	Open Beach	Open Water	Shrub Sand Dune	Treed Sand Dune	Shallow/Turbid Water
Built-Up Area Impervious		(1.83, 2.00)	(1.97, 2.00)	(1.83, 1.97)	(1.98, 2.00)	(1.88, 1.97)
Open Beach	(1.88, 2.00)		(2.00, 2.00)	(1.99, 1.99)	(2.00, 2.00)	(1.99, 2.00)
Open Water	(1.97, 2.00)	(2.00, 2.00)		(2.00, 2.000)	(1.99, 2.00)	(1.93, 2.00)
Shrub Sand Dune	(1.82, 1.97)	(2.00, 2.00)	(2.00, 2.00)		(1.93, 2.00)	(2.00, 2.00)
Treed Sand Dune	(1.99, 2.00)	(2.00, 2.00)	(1.99, 2.00)	(1.93, 2.00)		(2.00, 2.00)
Shallow/Turbid Water	(1.88, 1.97)	(1.99, 2.00)	(1.94, 2.00)	(2.00, 2.00)	(1.99, 2.00)	

NOTE: Quantitative measures of spectral separability are presented in the above chart as follows: (Jeffries-Matusita, Transformed Divergence).

Table 4.8: Class Distribution Summary

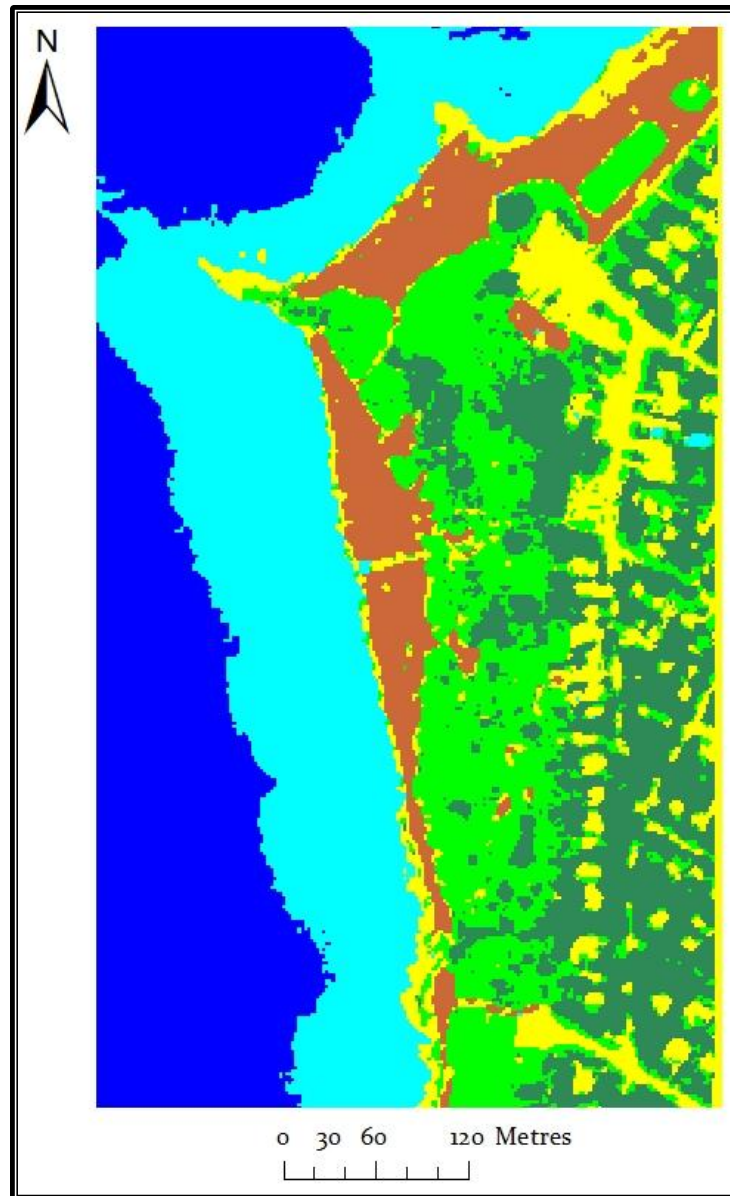
Class	Number of Points	Percentage (%)	Area (m ²)
Built-Up Area Impervious	9,576	13.0%	38,554.7
Open Beach	5,808	7.9%	23,384.1
Open Water	17,280	23.5%	69,572.5
Shrub Sand Dune	11,655	15.7%	46,478.3
Treed Sand Dune	11,422	15.5%	45,987.1
Shallow/Turbid Water	18,014	24.5%	72,527.7

A majority of the six information classes had producer's and user's accuracies greater than 95%. The exceptions were "Built-Up Area Impervious" with a user's accuracy of 84% and "Shallow/Turbid Water" with a producer's accuracy of 93%. The "Built-Up Area Impervious" class had the highest error of commission of all the information classes at 16%. As evident from the error matrix summarized in **Table 4.9**, several pixels notably from the "Open Beach" and "Shallow Turbid Water" information classes were committed to the "Built-Up Area Impervious" class. The minor confusion between "Built-Up Area Impervious and Open Sand" is particularly noticeable in the upper right-hand corner of the classified image where several pixels have been erroneously classified as "Built-Up Area Impervious" rather than "Open Sand". This is not surprising, given this particular area of the beach consists of less fine, rockier sand. Accordingly, the pixels have spectral signatures similar to those in the "Built-Up Area Impervious" information class.

In terms of user's accuracies, "Open Beach" and "Shallow Turbid Water" were well-classified at 100% and 98%, respectively, with the only inaccuracies due to errors of omission (producer's accuracies of 98% and 93%, respectively). This result is not surprising given the close proximity of these respective information classes to one another along the shoreline. In addition, as evident from the error matrix, several pixels were omitted from the "Shallow Turbid Water" class amid slight confusion with the "Built-Up Area Impervious" and "Open Water" classes. Both these results were not unexpected given that some open water areas contain shallow and turbid areas within them; and the turbidity of the water, especially along the shoreline, resulted in pixels that were spectrally similar with the surrounding built-up environment (e.g., roofs of some buildings).

The results of this research project indicate that GeoEye-1 imagery and the maximum-likelihood classification algorithm can be used to map the Chantry Dune system at the community series level of the ELC for southern Ontario with a high degree of accuracy. The overall classification accuracy was 97.3% with a Kappa coefficient of 97%. Therefore, the classification result has achieved an acceptable level of accuracy given the standard is at least 80-85% or higher (Ismail and Jusoff, 2008; Jansen et al., 2008; Jensen, 2005). Overall, qualitative and quantitative analyses of the classification result indicated that the maximum-likelihood classification algorithm was successful in mapping the Chantry Dune system. The user's and producer's accuracies for all information classes were over 80% and 90%, respectively. Errors of omission were all below 10%, with the highest being "Shallow Turbid Water" at 7%. "Built-Up Area Impervious" had the highest error of commission at 16%, while the remaining information classes had errors of commission of 2% or lower. Given the complexity and heterogeneity of the Chantry Dune system, the final classification result exceeded expectations. The high classification accuracies can be attributed to several factors, including the spatial and spectral resolution of the GeoEye-1 imagery, data from the field study, and knowledge of the study area.

The classification result provides an accurate map of the Chantry Dune system that can be used by the municipality and local residents to inform dune management and stewardship efforts. Due to the spatial and spectral resolution of the GeoEye-1 sensor, and the heterogeneity of the dune system, it was not possible to map the dune system at a more detailed level of the ecological land classification.



Legend	
 Built-Up Area Impervious	 Open Beach
 Open Water	 Shrub Sand Dune
 Treed Sand Dune	 Shallow/Turbid Water

Figure 4.15: Land-use/land-cover map of the Chantry Dune system derived from the application of the maximum-likelihood algorithm to four bands of GeoEye-1 data. A final version of this map appears in **Appendix G**.

Table 4.9: Error Matrix for the Maximum-Likelihood Classification of the GeoEye-1 Dataset

	Reference Data						
	Built-Up Area Impervious	Open Beach	Open Water	Shrub Sand Dune	Treed Sand Dune	Shallow/Turbid Water	Total
Classification Result	Built-Up Area Impervious	729	36	2	8	17	865
	Open Beach	6	1503	0	0	0	1509
	Open Water	0	0	1855	0	41	1896
	Shrub Sand Dune	10	1	0	1325	9	1352
	Treed Sand Dune	2	0	0	9	2035	2046
	Shallow/Turbid Water	7	1	15	0	3	1598
	Total	754	1541	1872	1342	2064	9292

Table 4.10: Summary of Classification Errors for the Maximum-Likelihood Classification Algorithm

Class	Omission error (%)	Commission error (%)	Producer's accuracy (%)	User's accuracy (%)
Built-Up Area Impervious	3.3	15.7	96.7	84.3
Open Beach	2.5	0.4	97.5	99.6
Open Water	0.9	2.2	99.1	97.8
Shrub Sand Dune	1.3	2.00	98.7	98.00
Treed Sand Dune	1.4	0.54	98.6	99.5
Shallow/Turbid Water	7.0	1.6	93.0	98.4

It is difficult to compare the results presented herein with previous research given this is the first known use of remote-sensing technologies to map and monitor this particular dune system. Nevertheless, as discussed in Chapter Two, remote sensing has been used extensively elsewhere to map dune ecosystems. Findings presented here are consistent with results of other studies, which suggest that hard classifiers, such as the maximum-likelihood algorithm, can be used to map dune systems accurately at the broad habitat level (Özdemir et al., 2005; Shanmugam et al., 2003). These outputs can be used to provide baseline data for dune management and conservation. However, the development of information outputs required to address management issues at a finer, more detailed scale, would likely require the use of sub-pixel classifiers and remote-sensing data with greater spatial and spectral resolutions than GeoEye-1, such as the Compact Airborne Spectrographic Imager, or CASI (Shanmugam et al., 2003). These are certainly possible avenues for future research as discussed in Chapter Five.

4.5 - Limitations of Research

It is important to note the limitations of this research project. First, the availability and quality of remote-sensing imagery from DigitalGlobe greatly influenced the selection of the 2005 and 2012 study dates. To accurately map and monitor the dune system, high resolution remote-sensing

imagery was required to meet this objective. Given the relative infancy of high resolution sensors, such as QuickBird and GeoEye-1, the limited availability of data for historical dates influenced the time period selected. While it would have been interesting to use historical imagery from the late 1980s to mid-1990s to demonstrate the change in vegetation cover over a broader period of time, the limited spatial and spectral resolution of available sensors (e.g., Landsat TM and ETM+) would not have been able to provide the level of detail required to meet the overall goal and objectives of this research project given a study site of 8 ha.

This project was also conducted within a financial framework that provided guidelines which subsequently influenced the overall goal and objectives of this project. The use of remote-sensing imagery acquired in 2015 to coincide with the field study, would have been ideal and would have permitted an analysis of vegetation change over a decade. However, this was not a feasible endeavour given the order size and prohibitive cost of new tasking orders (DigitalGlobe, 2014c). Nevertheless, this research project does provide an important set of exploratory data and analysis that validates the approach used and provides the foundation for a larger project in the near future with greater financial resources.

While this research project has produced a number of information outputs that provide baseline data for the management and stewardship of the Chantry Dune system, it does not provide information and analysis regarding the height of dunes within the system and their changes over time. As previously highlighted in this chapter, the growth in the height of the dunes along Harmer Street is an important and complex management issue. Further data and analysis of these changes would be beneficial in addressing some residents' concerns and perhaps is an opportunity for future research (see Chapter 5).

The LULC classes used for this research study are another limitation. While the ELC for southern Ontario was used because of its increasing prominence in ecosystem management in Ontario (Lee et al., 1998), the standardized classification system was too coarse for this particular study. For example, the ELC presented challenges for classifying dunes without shrubs and trees which is a noticeably distinct land-cover. The use of a more detailed classification system, perhaps one specifically tailored to reflect the LULC classes found in the Chantry Dune system, may have been more ideal. The spatial and spectral resolutions of GeoEye-1 also influenced the use of a coarse classification result. In order to obtain an acceptable level of accuracy, the use of broad LULC classes was therefore required. This limitation may be addressed in future research projects with the use of remote-sensing data with greater spatial and spectral resolutions; further discussion on this topic is provided in Chapter 5.

4.6 - Chapter Summary

This chapter presented the results and a discussion of the analytical methods performed on the QuickBird and GeoEye-1 remote-sensing data. These analytical methods included the development of multi-temporal NDVI images, post-classification change-detection analysis of the NDVI images, and the supervised classification of the GeoEye-1 data using the maximum-likelihood classification algorithm.

The multi-temporal NDVI images revealed increased dune vegetation growth throughout the Chantry Dune system from 2005-2012. In addition, the post-classification change detection analysis revealed that NDVI values remained relatively unchanged or increased slightly from 2005-2012. The observed increase in dune vegetation throughout the dune system is likely attributed to several factors including low water levels, which encourage dune grass to migrate lake-ward, and the town's management practices which include education and local awareness.

In some areas, the increase in dune vegetation has resulted in some overgrowth onto dune pathways and limited the area of the beach. For some lakefront property owners, the increased vegetation growth and increase in the dune vegetation height along Harmer Street has obscured their scenic view of Lake Huron and some have resorted to removing this vegetation themselves. This remains an important and complex management and stewardship concern for the SRA, Town of Saugeen Shores, MNR, and Saugeen Valley Conservation Authority moving forward.

The results of the supervised image classification indicated that the maximum-likelihood classification algorithm can be applied to GeoEye-1 imagery and produce an accurate information output to inform management and stewardship decisions. Specifically, the maximum-likelihood algorithm was able to classify the Chantry Dune system at the community series level of the ELC for southern Ontario with an overall accuracy of 97% and a Kappa coefficient of 97%. This classified map can be used by stakeholders to inform broad management and stewardship initiatives within the Chantry Dune system. Finally, the chapter concluded with a discussion on the limitations of this research project, including the availability of remote-sensing data. The final chapter of this thesis will provide a summary of the research project, identify areas for future research, and include some concluding comments regarding dune management and stewardship moving forward.

Chapter Five: Conclusions

5.1 - Introduction

The final chapter of this thesis aims to provide an overall summary of the current research project, including the purpose, overall goal, and objectives. Discussion then shifts towards the review of the literature and the data, methodology, and analytical operations performed. The results of the multi-temporal NDVI images and post-classification change-detection analysis of the QuickBird and GeoEye-1 imagery are then reviewed. This is followed with a summary of the supervised image classification results, which involved the application of the maximum-likelihood classification algorithm to the GeoEye-1 data. Possible avenues for future research are also highlighted and examined. Finally, the chapter concludes with some final thoughts on the conservation and stewardship of the Chantry Dune system moving forward.

5.2 - Summary

The purpose of this research project was to monitor dune vegetation change at the Chantry Dune system in Southampton, Ontario. In particular, the research question was: *What are the patterns of change in vegetation cover within the Chantry Dune system from 2005 to 2012?* The overall goal of this research project was to provide information to local government, citizens, and stakeholders regarding changes in vegetation cover within the Chantry Dune system to better inform management decisions. This goal was achieved through the following objectives:

- To produce multi-temporal NDVI images from 2005-2012;
- To determine the patterns of change in vegetation cover within the Chantry Dune system from 2005-2012 using the post-classification comparison change-detection technique;
- and

- To produce an accurate LULC map of the Chantry Dune system using a supervised classification technique.

This research project reviewed the literature pertaining to the use of remote-sensing technologies in the mapping and monitoring of coastal dune vegetation to highlight important themes, concepts, and trends. In addition, the literature review situated the current research project within the broader academic literature. Notably, the review of the literature revealed a lack of research pertaining to the use of remote-sensing technologies to map and monitor coastal dunes vegetation in the Great Lakes Basin. Thus, this research project contributes to an underdeveloped area within the academic literature.

The data and methodology used in this research project were then discussed, including the data acquisition process, image preprocessing operations, and the analytical methods performed on the remotely sensed datasets. In particular, this included the production of NDVI images for the QuickBird and GeoEye-1 images, and post-classification change-detection analysis. The maximum-likelihood classification algorithm was applied to the GeoEye-1 imagery from July 2012 to produce an accurate land-use/land-cover map of the Chantry Dunes. Lastly, accuracy assessment of the supervised classification result was performed.

The research project successfully determined the spatio-temporal patterns in vegetation change from 2005 to 2012. Specifically, the multi-temporal NDVI images revealed increased dune vegetation growth throughout the Chantry Dune system while the post-classification change-detection analysis highlighted that NDVI values remained relatively unchanged or increased slightly from 2005 to 2012. The results of the supervised image classification indicated that the maximum-likelihood classification algorithm can be applied to GeoEye-1 imagery of the

Chantry Dunes and produce an accurate land-use/land-cover map that may be used to inform management and stewardship decisions. In addition, the land-use/land-cover map provides baseline data which may be used in further research initiatives.

5.3 - Areas for Future Research

The Chantry Dune system affords itself to numerous and exciting opportunities for future research. One such area of future research may involve the use of LiDAR technology to investigate and monitor sand dune height along the Harmer Street section of the Chantry Dune system. As previously discussed, this is a prominent concern among Harmer Street residents given the increased height in the dunes and vegetation growth have impacted their aesthetic views of Lake Huron (Town of Saugeen Shores, 2015b; Town of Saugeen Shores, 2013). LiDAR technology could be used to provide three-dimensional models of the sand dunes and monitor their growth over time. These datasets and models could be used by coastal managers to educate local citizens and decision-makers of the dynamic processes that occur naturally within the dune system.

Further studies involving hyperspectral data, acquired by sensors such as CASI and aerial drones, can provide datasets at greater spatial and spectral resolutions than traditional satellite data (e.g., GeoEye-1). These sensors collect hundreds of bands of data across the EMS and thus are able to better differentiate between the reflectance characteristics of Earth-surface features, including various dune vegetation species. Accordingly, airborne remote-sensing imagery, including data acquired from aerial drones, can provide the necessary resolutions to map and monitor complex, heterogeneous dune ecosystems at a more detailed spatial scale (Zhang et al., 2012; Shanmugam et al., 2003; Lucas et al., 2002). This can result, for example, in the

production of detailed vegetation maps which can provide useful information on the spatial distribution of dune vegetation at the species level.

Advancements in satellite technology can provide imagery at greater spatial and spectral resolutions. For example, WorldView-3 acquires eight bands of multispectral data (with 1.24 m pixel sizes) from the visible and infrared portions of the electromagnetic spectrum, including coastal and yellow bands. In addition, WorldView-3 also has a red edge band and two bands acquiring data within the NIR portion of the spectrum (DigitalGlobe, 2016). These bands, especially the red edge band and two NIR bands, can provide further detail necessary to differentiate between the various vegetation species present within a dune system and produce accurate information outputs (Xie et al., 2008). The use of soft classification approaches, such as SMA and fuzzy classifiers, may also be used in conjunction with these aforementioned spatial datasets (i.e., WorldView-3, aerial drones, and CASI) to provide more detailed mapping outputs (Lillesand et al., 2008; de Lange, 2004).

The increasing concern of invasive species and their threat to Great Lakes ecosystems, including dune vegetation, is another future research opportunity that can be investigated using remote-sensing technologies. *Phragmites australis*, for example, is an invasive plant that has had negative impacts in the Great Lakes Basin, including habitat degradation, competition with native flora and fauna species, reduction of biological diversity, and obscured shoreline views which impact property values (Bourgeau-Chavez et al., 2013; Tulbure et al., 2007; Wilcox et al., 2003). Concerns regarding *Phragmites australis* have also been highlighted by town officials in several documents, including the Waterfront Master Plan and the Beach Maintenance Plan (Town of Saugeen Shores, 2015a; Town of Saugeen Shores, 2013). Results of this research project can be used as baseline data in future projects, in combination with hyperspectral data,

WorldView-3 satellite imagery, and data acquired by aerial drones, to produce maps of areas where *Phragmites australis* are a concern to inform and guide their removal.

Lastly, another possible research initiative would be the use of participatory mapping to incorporate local knowledge into the discussion and production of information products for dune management and stewardship. Civic participation is a notable topic within the field of sustainability science, and includes the importance and challenges of citizen inclusion in the production and application of scientific knowledge. In this regard, scientists and policy makers are no longer the exclusive participants in the decision-making process; rather, citizens are viewed as important agents in this domain (Bäckstrand, 2003). The use of remote-sensing technologies and information outputs can be used to bring awareness to the health of dune vegetation and its vital role to the overall health of the dune system. Hopefully this understanding will lead to increased civic engagement and participation in dune management initiatives. As discussed by Peach (2006), the strong public participation in the development of various dune conservation projects and the continued activism among residents and the SRA in dune management, provides several exciting opportunities for future public participatory research in the area.

The use of participatory mapping is becoming increasingly common in the field of sustainability science and natural resource management as it permits local knowledge to be collaboratively integrated in the decision-making process, which provides more complete information for planning and the development of management and stewardship strategies. In addition, the early inclusion of local citizens in the participatory mapping and decision-making process can improve trust and buy-in of management initiatives (Levine and Feinholz, 2015; Dunn, 2007; Berkes, Colding, and Folke, 2000). Given the activism and support of Southampton

residents in previous dune management initiatives, further incorporation and engagement of citizens through participatory mapping would be a logical and beneficial next-step. The collaboration and contributions of local residents through participatory mapping initiatives can provide new insights into the various processes operating within socio-environmental systems and increase the local acceptance of conservation initiatives (Lauer and Aswani, 2008). For example, remote sensing can be combined with participatory action research to further monitor the dunes, understand the challenges surrounding the management of a dynamic coastal dune system, and integrate this information into planning and adaptive ecosystem management. Discussion with local residents can help in the classification of vegetation types, gain a better understanding of how residents' perceptions of the dune system has changed over time, augment research initiatives, increase local capacity, result in desirable outcomes, and improved management and stewardship practices. It is important to note the above mentioned possibilities for future research by no means represent an exhaustive list of possible future research endeavours.

5.4 - Conclusions: Moving Forward

This research project demonstrated that remote-sensing technologies can be used to accurately map and monitor coastal dune vegetation and produce information outputs useful for stewardship and conservation purposes. In particular, multi-temporal NDVI images and post-classification change-detection analysis can provide valuable information regarding patterns of vegetation change across spatial and temporal scales. Remote-sensing data can also be used to successfully and accurately produce a LULC map of the Chantry Dunes at the community series level of the ELC for southern Ontario that provides broad information for management and stewardship

purposes. Lastly, this research project has provided baseline data useful for future research and management initiatives; and a methodological template that can be repeated by other researchers.

The results and information of this research project can be used by a variety of local stakeholders in the management and stewardship of the Chantry Dune system. Coastal managers can make use of the results and information to better understand the geomorphological approaches occurring within the Chantry Dune system and communicate this knowledge to local stakeholders. Understanding the complex and dynamic processes that occur within coastal dune systems and their implications for dune management and adjacent property owners, needs to be clearly explained in order to facilitate decision-making. This process is not without its challenges and there may be residents and local politicians who may be steadfast in their views and unwilling to manage these systems based on best practices and the academic literature. To address such challenges, the sustainability science literature pertaining to citizen science, environmental governance, and knowledge mobilization may be useful in this regard (Miller, 2013; Lemos and Agrawal, 2006; Bäckstrand, 2003).

As discussed above, the use of participatory processes may be used to engage local citizens as active and valued participants in the decision-making process. Public participation should be seen as an opportunity in which ideas, knowledge, and solutions can be expressed in a bi-directional manner. Research has revealed that the engagement of stakeholders can result in increased dialogue, understanding, trust, consensus-building, and transparency which can result in favourable outcomes for ecosystem management (Chuenpagdee et al., 2004; Bäckstrand, 2003; McCool and Guthrie, 2001). The engagement of local citizens in the decision-making process may involve a variety approaches including but not limited to, education, workshops, and discussion forums. The use of participatory remote sensing may also be one way to engage

local citizens into the research and decision-making process; this may involve the collection of validation and growth truth points, and the identification of areas of concern within the Chantry Dune system. Regardless of the approach employed to engage citizens, it is imperative to ensure people feel that they have a voice, and ownership in the decision-making process as this has proven to be essential in engaging the public (Lemos and Agrawal, 2006).

The outcomes of the current research project can also be used by local decision-makers, including the Town of Saugeen Shores and politicians, to inform and refine beach management plans and waterfront plans which have recently been developed. The continued education of the local population and tourists, as to the dune system's important functions, is an important endeavour which may be facilitated through pamphlets, open houses, and the installation of additional signs. Finally, the town in collaboration with researchers and local citizens could also conduct a more comprehensive study to investigate the overall health of the ecosystem. It is important to note that in their efforts to manage the dune system in collaboration with local stakeholders, the municipality must operate within financial and legislative parameters which present limitations and challenges. In addition, municipal politics presents some challenges for dune management, including the unfortunate situation whereby some politicians may base management decisions due to pressures by constituents with a view to get re-elected; this short sightedness is not compatible with the long-term management vision required to ensure the sustainability of the dune system.

The management and stewardship of a waterfront is an inherently complex endeavour given the variety of stakeholders' interests and the need to balance the environmental, economic, and social functions of the waterfront. Management and stewardship initiatives are further complicated by the broader context of relevant legislation and statutes (e.g., the Endangered

Species Act 2007), and by the uncertainties associated with the impacts of climate change and possible longer periods of lower water levels, all of which will impact the dune system.

Moreover, the tension between the aesthetic and ecosystem function of the dune system also presents challenges for management and stewardship efforts. The management and stewardship of the Chantry Dunes is therefore a delicate balance between addressing the concerns of adjacent property owners, the tourism economy, and the overall health and sustainability of the dune system. While there are a variety of stakeholders in the management of the Chantry Dunes system, the Town of Saugeen has an engaged and active citizenry who are knowledgeable about the ecological and economic importance of the dune system. This engagement has contributed to the success of management strategies in the past and will likely influence the outcome of future management strategies.

Accordingly, the conservation and stewardship of these fragile systems is not limited to a single academic discipline, institution, or stakeholder group. While remote-sensing technologies can provide useful information for dune management practices it represents only one “piece of the puzzle” as it pertains to the functions of dune systems and overall dune conservation. Dune management and conservation is a dynamic, complex practice that requires a transdisciplinary approach that incorporates input, knowledge, and solutions from a variety of disciplines, institutions, and stakeholders to provide a holistic approach to management. Thus, important concepts from the sustainability science literature including citizen science, co-construction of knowledge, and participatory processes will be critical to the success of future management and conservation initiatives.

Overall, the results of this research project reveal how the application of remote-sensing technologies can be used to expand stakeholder knowledge of the Chantry Dune system, improve

decision-making, and produce accurate outputs to inform and guide management and stewardship decisions. In addition, these technologies can be used in conjunction with information and data from a variety of other disciplines, institutions, and stakeholders to facilitate the collaborative management of the Chantry Dune system. Given the Town of Saugeen Shores is recognized as a leader in dune conservation in Ontario, the inclusion of remote-sensing technologies and the use of derived information outputs in their dune conservation efforts will contribute to this continued recognition and ensure the overall sustainability and vitality of the beach ecosystem moving forward.

References

- Adam, E., Mutanga, O., and Rugege, D. 2010. Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review. *Wetlands Ecology and Management* 18: 281-296.
- Ahnert, F. 1998. *Introduction to Geomorphology*. London, UK: John Wiley & Sons Ltd.
- Alphan, H. 2005. Perceptions of coastline changes in river deltas: southeast Mediterranean coast of Turkey. *International Journal of Environment and Pollution* 23(1): 92-102.
- Andersen, U.V. 1995. Resistance of Danish coastal vegetation types to human trampling. *Biological Conservation* 71: 223-230.
- Angel, J. R., and Kunkel, K. E. 2010. The response of Great Lakes water levels to future climate scenarios with an emphasis on Lake Michigan-Huron. *Journal of Great Lakes Research* 36: 51-58.
- Bäckstrand, K. 2003. Civic science for sustainability: reframing the role of experts, policy-makers and citizens in environmental governance. *Global Environmental Politics* 3(4): 24-41.
- Bagnold, R. 1954. *The Physics of Blown Sand and Desert Dunes*. New York, NY: William Morrow & Company.
- Bannari, A., Morin, D., Bonn, F., and Huete, A. R. 1995. A review of vegetation indices. *Remote Sensing Reviews*, 13(1): 95-120.
- Berberoglu, S., Alphan, H., and Yilmaz, K. T. 2003. A remote sensing approach for detecting agricultural encroachment on the eastern Mediterranean coastal dunes of Turkey. *Turkish Journal of Agriculture and Forestry* 27(3): 135-144.
- Berkes, F., Colding, J., and Folke, C. 2000. Rediscovery of traditional ecological knowledge as adaptive management. *Ecological Applications*, 10(5): 1251-1262.
- Bonanno, S.E., Leopold, D.J., and St. Hilaire, L.R. 1998. Vegetation of a freshwater dune barrier under high and low recreational use. *Journal of the Torrey Botanical Society* 125(1): 40-50.
- Bourgeau-Chavez, L. L., Kowalski, K. P., Carlson Mazur, M. L., Scarbrough, K. A., Powell, R. B., Brooks, C. N., Huberty, B., Jenkins, L. K., Banda, E. C., Galbraith, D. M., Laubach, Z. M., and Riordan, K. 2013. Mapping invasive *Phragmites australis* in the coastal Great Lakes with ALOS PALSAR satellite imagery for decision support. *Journal of Great Lakes Research Supplement* 39: 65-77.
- Bowles, J.M., and Maun, M. A. 1982. A study of the effects of trampling on the vegetation of Lake Huron sand dunes at Pinery Provincial Park. *Biological Conservation* 24: 273-283.

- Broome, S. W., Seneca, E. D., Woodhouse, W. W. 1982. *Building and Stabilizing Coastal Dunes with Vegetation*. University of North Carolina Sea Grant College Publication UNC-SG-82-05.
- Brown, D. G., and Arbogast, A. F. 1999. Digital photogrammetric change analysis as applied to active coastal dunes in Michigan. *Photogrammetric Engineering and Remote Sensing* 65(4), 467-474.
- Campbell, J. B. 2007. *Introduction to remote sensing* (4th ed.). New York, NY: Guilford Press.
- Canada Centre for Remote Sensing. (2008, January 29). *Tutorial: Fundamentals of Remote Sensing Image Interpretation & Analysis – Image Transformations*. Retrieved March 1, 2015, from <http://www.nrcan.gc.ca/earth-sciences/geography-boundary/remote-sensing/fundamentals/2062>.
- Cho, H. J., Mishra, D., and Wood, J. 2012. “Remote Sensing of Submerged Aquatic Vegetation”, in *Remote Sensing - Applications*, Dr. Boris Escalante (Ed.), ISBN: 978-953-51-0651-7, InTech, Available from: <http://www.intechopen.com/books/remote-sensing-applications/remote-sensing-of-submerged-aquaticvegetation>.
- Christopherson, R. W., and Byrne, M. L. 2006. *Geosystems: An Introduction to Physical Geography, Canadian Edition*. Toronto, Ontario: Pearson Education Canada.
- Chuenpagdee, R., Fraga, J., and Euan-Avila, J. 2004. Progressing toward comanagement through participatory research. *Society and Natural Resources* 17(2): 147–161.
- Clark, A., and Peach, G. 2010. *Lake Huron Coastal Dune Plants Guide*. Prepared by the Lake Huron Centre for Coastal Conservation. Blyth, Ontario.
- Clark, R. N., Swayze, G. A., Livo, K. E., Kokaly, F., Sutley, S. J., Dalton, J. B., McDougal, R. R., and Gent, C. A. 2003. Imaging spectroscopy: Earth and planetary remote sensing with the USGS Tetracorder and expert systems. *Journal of Geophysical Research* 108(E12): 5-1 to 5-44.
- Cochard, R., Ranamukhaarachchi, S. L., Shivakoti, G. P., Shipin, O. V., Edwards, P. J., and Seeland, K. T. 2008. The 2004 tsunami in Aceh and southern Thailand: a review on coastal ecosystems, wave hazards and vulnerability. *Perspectives in Plant Ecology Evolution and Systematics* 10(1): 3–40.
- Congalton, R. G. and Green, K., 2009. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Second Edition. Boca Raton, FL: CRC Press.
- Congalton, R. G. 1991. A review of assessing the accuracy of classification of remotely sensed data. *Remote Sensing of Environment* 37: 35-46.
- Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., and Lambinint, E. 2004. Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing* 25(9): 1565-1596.

- Davenport, J., and Davenport, J. L. 2006. The impact of tourism and personal leisure transport on coastal environments: A review. *Estuarine, Coastal and Shelf Science* 67: 280-292.
- Dech, J. P., Maun, M. A., and Pazner, M. I. 2005. Blowout dynamics on Lake Huron sand dunes: Analysis of digital multispectral data from colour air photos. *Catena* 60(2):165-180.
- de Lange R., van Til, M., and Dury, S. 2004. The use of hyperspectral data in coastal zone vegetation monitoring. *EARSeL eProceedings* 3(2): 143-153.
- DigitalGlobe. 2016. *WorldView-3 Data Sheet*. Retrieved March 17, 2015 from http://global.digitalglobe.com/sites/default/files/DG_WorldView3_DS_forWeb_0.pdf
- DigitalGlobe. 2014a. *GeoEye-1 Data Sheet*. Retrieved March 15, 2015 from https://www.digitalglobe.com/sites/default/files/DG_GeoEye1.pdf
- DigitalGlobe. 2014b. *QuickBird Data Sheet*. Retrieved March 15, 2015 from <https://www.digitalglobe.com/sites/default/files/QuickBird-DS-QB-Prod.pdf>
- DigitalGlobe. 2014c. *Standard Imagery Data Sheet*. Retrieved May 14, 2015 from http://global.digitalglobe.com/sites/default/files/StandardImagery_DS_10-14_forWeb.pdf
- D'Ulisse, A., and Maun, M.A. 1996. "Population Ecology of *Cirsium pitcheri* on Lake Huron Sand Dunes. II. Survivorship of Plants." *Canadian Journal of Botany* 74: 1701-07.
- Dunn, C. E. 2007. Participatory GIS--a people's GIS? *Progress in Human Geography* 31(5): 616-637.
- Efe, R., and Tagil, S. 2008. The use of multi-temporal and multispectral Landsat data to determine change detection around Tuz Lake on Seyhan Delta. *Fresenius Environmental Bulletin* 17(5): 577-583.
- El-Asmar, H. M., and Al-Olayan, H. A. 2013. Environmental impact assessment and change detection of the coastal desert along the Central Nile Delta Coast, Egypt. *International Journal of Remote Sensing Applications* 3(3): 159-170.
- Emery, Sarah M. and Rudgers, Jennifer A. 2009. Ecological Assessment of Dune Restorations in the Great Lakes Region. *Restoration Ecology* 18, 184-194.
- Environment Canada. 2015a. Canadian Climate Normals 1961-1990 Station Data - Southampton, Ontario. Retrieved February 3, 2015 from http://climate.weather.gc.ca/climate_normals/results_1961_1990_e.html?stnID=988&prov=ON&lang=e&dCode=&dispBack=1&StationName=SOUTHAMPTON&SearchType=Contains&province=ALL&provBut=Go&month1=0&month2=12

- Environment Canada, 2015b. Hourly Data Report for July 9, 2005 - Wiarton, Ontario. Retrieved December 10, 2015 from http://climate.weather.gc.ca/climateData/hourlydata_e.html?timeframe=1&Prov=&StationID=4538&dlyRange=1947-07-01|2014-11-05&cmdB1=Go&cmdB2=Go&Year=2005&Month=7&Day=9
- Environment Canada, 2015c. Hourly Data Report for July 28, 2012 - Wiarton, Ontario. Retrieved December 10, 2015 from http://climate.weather.gc.ca/climateData/hourlydata_e.html?timeframe=1&Prov=&StationID=4538&dlyRange=1947-07-01%7C2014-11-05&cmdB1=Go&cmdB2=Go&Year=2012&Month=7&Day=28&cmdB1=Go
- Environment Canada and the U. S. Environmental Protection Agency. 2014. *State of the Great Lakes 2011*. Cat No. En161-3/1-2011E-PDF. EPA 950-R-13-002. [Available at <http://binational.net>].
- Environmental Commissioner of Ontario. 2013. Ontario's Forgotten Habitats: Tallgrass Communities, Alvars and Coastal Dunes. *Serving the Public, ECO Annual Report, 2012/13*. Toronto: Queen's Printer for Ontario.
- Foody, G. M. 2008. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* 80: 185-201.
- Franklin, S.E., and Giles, P.T., 1995. Radiometric processing of aerial and satellite remote-sensing imagery. *Computers and Geosciences* 21(3): 413–423.
- Gauthier, M., Crowe, E., Hawke, L., Emery, N., Wilson, P., and Freeland, J., 2010. Conservation Genetics of Pitcher's Thistle (*Cirsium pitcheri*), an Endangered Great Lakes Endemic. *Botany* 88(3): 250-57.
- Geleen, L.H.W.T., 1997. Landscape succession in the Haasvelderduinen (in the past 50 years). In: Garcia Novo, F., Crawford, M.M., Cruz Diaz Barradas, M. (Eds.), *The Ecology and Conservation of European Dunes*. Universidad de Sevilla, Sevilla, pp. 268–275.
- Gonçalves, G. Duro, N., Sousa, E., Pinto, L., and Figueiredo, I. 2014. Detecting changes on coastal primary sand dunes using multi-temporal Landsat Imagery. *Proceedings. SPIE 9244, Image and Signal Processing for Remote Sensing XX*, 924420 (October 29, 2014).
- Hantson, W., Kooistra, L., and Slim, P. A. 2012. Mapping invasive woody species in coastal dunes in the Netherlands: a remote sensing approach using LIDAR and high-resolution aerial photographs. *Applied Vegetation Science* 15(4): 536-547.
- Hartog, M., van der Meulen, F., Jongejans, J., 1992. Dune landscape development and changing groundwater regime: quantitative landscape succession with the help of a GIS. In: Carter, R.W.G., Curtis, T.G.F., Sheehy-Skeffington, M.J. (Eds.), *Coastal Dunes: Geomorphology, Ecology and Management for Conservation*. A.A.Balkema, Rotterdam, pp. 119– 129.

- Holben, B. N. 1986. Characteristics of maximum-value composite images from temporal AVHRR data. *International Journal of Remote Sensing* 7(11): 1417-1434.
- Hungenholtz, C. H., Levin, N., Barchyn, T. E., and Baddock, M. C. 2012. Remote sensing and spatial analysis of Aeolian sand dunes: A review and outlook. *Earth-Science Reviews* 111: 319-334.
- Ismail, M. H., and Jusoff, K. 2008. Satellite data classification accuracy assessment based from reference dataset. *International Journal of Environmental, Chemical, Ecological, Geological, and Geophysical Engineering* 2(3): 23-29.
- Jalava, J. V., Jones, J., and Ben-Oliel, R. 2003. Background Report to the Pitcher's Thistle-Lake Huron Coastal Dune Grasslands Recovery Strategy. Lake Huron Coastal Dune Systems Recovery Team. Parks Canada and Ontario Ministry of Natural Resources. 106 pp.
- Jansen, L. J. M., Bagnoli, M., and Focacci M. 2008. Analysis of land-cover/use change dynamic in Manica Province in Mozambique in a period of transition (1990-2004). *Forest Ecology and Management* 254: 308-326.
- Jensen, J. R. 2007. *Remote sensing of the environment: An earth resource perspective* (2nd ed.). Upper Saddle River, NJ: Pearson Prentice Hall, Inc.
- Jensen, J. R. 2005. *Introductory digital image processing* (3rd ed.). Upper Saddle River, NJ: Prentice- Hall, Inc.
- Jerneck, A., L. Olsson, B. Ness, S. Anderberg, M. Baier, E. Clark, T. Hickler, A. Hornborg, A. Kronsell, E. Lövbrand, and J. Persson. 2011. Structuring sustainability science. *Sustainability Science* 6: 69-82.
- Jollineau, M. Y., and Howarth, P. J. 2008. Mapping an inland wetland complex using hyperspectral imagery. *International Journal of Remote Sensing* 29(12): 3609-3631.
- Jones, H. G., and Vaughan, R. A. 2010. *Remote sensing of vegetation: Principles, techniques, and applications*. Oxford, New York: Oxford University Press.
- Jungerius, P.D., and Schoonderbeek, D., 1992. The use of Leica Quantimet 970 for scanning blowout development on sequential airphotos of the 'Dunes de Slack' N.W. France. *Catena* (Suppl. 23): 59-73.
- Jungerius, P.D., van der Meulen, F., 1989. The development of dune blowouts, as measured with erosion pins and sequential airphotos. *Catena* (16): 369-376.
- Kates, R. W. 2011. What kind of a science is sustainability science? *PNAS* 108(49): 19449-19450.
- Kempeneers, P., Deronde, B., Provoost, S., and Houthuys, R. 2009. Synergy of airborne digital camera and Lidar data to map coastal dune vegetation. *Journal of Coastal Research* Special Issue 53: 73-82

- Klemas, V. 2011. Remote sensing techniques for studying coastal ecosystem: An overview. *Journal of Coastal Research* 27(1): 2-17.
- Kwarteng, A. Y., and Al-Ajmi, D. 1996. Using Landsat Thematic Mapper data to detect and map vegetation changes in Kuwait. *International Archives of Photogrammetry and Remote Sensing*, Volume 31, Part B7: 398-405.
- Lake Huron Centre for Coastal Conservation. 2012. Beach Stewardship and Grassroots Programs: The “trilogy approach”. Retrieved September 9, 2014 from <http://www.glin.net/glba/pdf/2012conf/Donnelly-LakeHuronCentre.pdf>
- Lang, D.J., A. Wiek, M. Bergmann, M. Stauffacher, P. Martens, P. Moll, M. Swilling, and C. J. Thomas. 2012. Transdisciplinary research in sustainability science: practice, principles, and challenges. *Sustainability Science* 7 (Supplement 1): 25–43.
- Lauer, M., and Aswani, S. 2008. Integrating indigenous ecological knowledge and multi-spectral image classification for marine habitat mapping in Oceania. *Ocean & Coastal Management* 51: 495-504.
- Lawrence, P. L. 1997. Ontario-Great Lakes Shoreline Management: An Update. *Coastal Management* 26: 93-104.
- Lawrence, P. L. 1995. Development of Great Lakes shoreline management plans by Ontario conservation authorities. *Ocean & Coastal Management* 26(3): 205-223.
- Lawrence, R. L., Means, J. E., Ripple, W. J., 1996. An automated method for digitizing colour thematic maps. *Photogrammetric Engineering & Remote Sensing* 62, 1245-1248.
- Leahy, M. G., Jollineau, M. Y., Howarth, P. J., and Gillespie, A. R. 2005. The use of Landsat data for investigating the long-term trends in wetland change at Long Point, Ontario. *Canadian Journal of Remote Sensing* 31(3): 240-254
- Lee, H., Bakowsky, W.D., Riley, J., Bowles, J., Puddister, M., Uhlig, P. and McMurray, S., 1998, Ecological Land Classification for Southern Ontario: First Approximation and its Application. Ontario Ministry of Natural Resources, Southcentral Science Section, Science Development and Transfer Branch. SCSS Field Guide FG-02 (Toronto: Government of Ontario).
- Lemos, M.C. and A. Agrawal. 2006. Environmental governance. *Annual Review of Environment and Resources* 31: 297-325.
- Lillesand, T. M., Kiefer, R. W., and Chipman, J. W. 2008. *Remote sensing and image interpretation* (6th ed.). New York, NY: John Wiley and Sons Inc.
- Lu, D., Mausel, P., Brondizio, E., and Moran, E. 2004. Change detection techniques. *International Journal of Remote Sensing* 25(12): 2365-2401.
- Lucas, N. S., Shanmugam, S., and Barnsley, M. 2002. Sub-pixel habitat mapping of a coastal dune ecosystem. *Applied Geography* 22(3): 253-270.

- Maiti, S., and Bhattacharya, A. K. 2011. A three-unit approach in coastal-change studies using Landsat images. *International Journal of Remote Sensing* 32(1): 209-229.
- Malatesta, L., Attorre, F., Altobelli, A., Adeeb, A., De Sanctis, M., Taleb, N. M., Scholte, P. T., and Vitale, M. 2013. Vegetation mapping from high-resolution satellite images in the heterogeneous arid environments of Socotra Island (Yemen). *Journal of Applied Remote Sensing* 7(1): 073527.
- Marine Heritage Society. 2012. Retrieved February 3, 2015 from <http://www.chantryisland.com/about.php>
- McCool, S. F., and Guthrie, K. 2001. Mapping the dimensions of successful public participation in messy natural resources management situations. *Society and Natural Resources* 14: 309-323.
- McDonald, A. J., Gemmell, F. M., and Lewis, P. E. 1998. Investigation of the utility of spectral vegetation indices for determining information on coniferous forests. *Remote Sensing of Environment* 66: 250–272.
- Midwood, J., and Chow-Fisher, P. 2012. Changes in aquatic vegetation and fish communities following 5 years of sustained low water levels in coastal marshes of eastern Georgian Bay, Lake Huron.
- Miller, T. R. 2013. Constructing sustainability science: Emerging perspectives and research trajectories. *Sustainability Science* 8: 279-293.
- Ontario Ministry of Natural Resources. 2011. *State of Ontario's Protected Areas Report* Toronto: Queen's Printer for Ontario.
- Özdemir, I., Asan, U., Koch, B., Yesil, A., Özkan, U. Y., and Hemphill, S. 2005. Comparison of Quickbird-2 and Landsat-7 ETM+ data for mapping of vegetation cover in Fethiye-Kumluova coastal dune in the Mediterranean region of Turkey. *Fresenius Environmental Bulletin* 14: 823-831.
- Peach, G. H. 2007. Beach Stewardship Guide for Huron-Kinloss. Blyth, Ontario: Lake Huron Centre for Coastal Conservation.
- Peach, G. H. 2006. Management of Lake Huron's beach and dune ecosystems. Building from the grassroots. *The Great Lakes Geographer* 13(1): 39-49.
- Peach, G. H. 2003. Beach and Dune Guidance Manual for Saugeen Shores. Blyth, Ontario: Lake Huron Centre for Coastal Conservation.
- Reinders, F. J., and Associates Ltd. 1987. Beach Stabilization and Marina Feasibility Study, Town of Southampton – February 1987. Southampton, Ontario: Author
- Saugeen Shores Chamber of Commerce. 2014. *Saugeen Shores 2014 Visitors Guide*. Port Elgin, Ontario: Saugeen Shores Chamber of Commerce.

- Schmidt, K. S., and Skidmore, A. K. 2003. Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment* 85: 92-108.
- Schowengerdt, R. A. 2007. Remote sensing: Models and methods for image processing (3rd ed.). Burlington, MA: Academic Press.
- Shanmugam, S., Lucas, N., Phipps, P., Richards, A., and Barnsley, M. 2003. Assessment of remote sensing techniques for habitat mapping in coastal dune ecosystems. *Journal of Coastal Research* 19(1): 64-75.
- Shellito, B. A. 2014. *Introduction to geospatial technologies*. (2nd edition). New York, NY: W. H. Freeman and Company.
- Sherman, D. J., and Bauer, B. O. 1993. Dynamics of beach-dune systems. *Progress in Physical Geography* 17(4): 413-447.
- Song, C., Woodcock, C. E., Seto, K. C., Lenney, M. P., and Macomber, S. A. 2001. Classification and change detection using Landsat TM data: When and how to correct atmospheric effects? *Remote Sensing of Environment* 75(2): 230-244.
- Spitzer, D. and Dirks, R. 1987. Solar Radiance Distribution in Deep Natural Waters Including Fluorescence Effects. *Applied Optics* 26(12): 2427-2430.
- State of the Lakes Ecosystem Conference (SOLEC). 2009. State of the Great Lakes 2009. Technical report prepared by Environment Canada and the United States Environmental Protection Agency. [Available at: <http://binational.net/wp-content/uploads/2014/11/En161-3-1-2009E.pdf>].
- Statistics Canada. 2012. Southampton, Ontario (Code 1176) and Ontario (Code 35) (table). Census Profile. 2011 Census. Statistics Canada Catalogue no. 98-316-XWE. Ottawa. Released October 24, 2012. <http://www12.statcan.gc.ca/census-recensement/2011/dp-pd/prof/index.cfm?Lang=E> (accessed February 9, 2015).
- Sutherland, S. 2011. Still no decision on dune height. *The Shoreline Beacon*. 20 September 2011. Retrieved from <http://www.shorelinebeacon.com/2011/09/20/still-no-decision-on-dune-height>
- Taylor, M. E., Gray, P. A., and Schiefer, K. 2006. Helping Canadians adapt to climate change in the Great Lakes Coastal Zone. *The Great Lakes Geographer* 13(1): 14-25.
- The Canadian Hydrographic Service. 2014. Monthly and Yearly Mean Water Levels. Ottawa, Ontario: Department of Fisheries and Oceans.
- Timm, B. C., and McGarigal, K. 2012. Fine-scale remotely-sensed cover mapping of coastal dune and salt marsh ecosystems at Cape Code National Seashore using Random Forests. *Remote Sensing of Environment* 127: 106-117.

- Townshend, J. R. G., Justice, C. O., Gurney, C., and McManus, J. 1992. The impact of misregistration on change detection. *IEEE Transactions on Geoscience and Remote Sensing* 30(5): 1054-1060.
- Town of Saugeen Shores. 2015a. Saugeen Shores Beach Maintenance Plan (Draft) August 2015. Port Elgin, Ontario: Town of Saugeen Shores.
- Town of Saugeen Shores. 2015b. Saugeen Shores Spring and Summer 2015 Municipal Guide. Port Elgin, Ontario: Town of Saugeen Shores Community Services Department.
- Town of Saugeen Shores. 2015c. Committee of the Whole Minutes. 24 August 2015.
- Town of Saugeen Shores. 2013. Waterfront Master Plan, August 2013. Port Elgin, Ontario: Town of Saugeen Shores.
- Town of Saugeen Shores. 2011. Committee of the Whole Minutes. 12 September 2011.
- Tulbure, M. G., Johnston, C. A., and Auger, D. 2007. Rapid invasion of a Great Lakes coastal wetland by non-native *Phragmites australis* and *Typha*. *Journal of Great Lakes Research* 33(3): 269-279.
- van Dijk, D. and Vink, D. R. 2005. Visiting a Great Lakes sand dune: The example of Mt. Pisgah in Holland, Michigan. *The Great Lakes Geographer* 12(2): 45-63.
- Wang, Y., Traber, M., Milstead, B., and Stevens, S. 2007. Terrestrial and submerged aquatic vegetation mapping in Fire Island National Seashore using high spatial resolution remote sensing data. *Marine Geodesy* 30: 77-95.
- Wilcox, D. A., Thompson, T. A., Booth, R. K., and Nicholas, J. R., 2007. Lake-level variability and water availability in the Great Lakes: U.S. Geological Survey Circular 1311.
- Wilcox, K. L., Petrie, S. A., Maynard, L. A., and Meyer, S. W. 2003. Historical distribution and abundance of *Phragmites australis* at Long Point, Lake Erie, Ontario. *Journal of Great Lakes Research* 29(4): 664-680.
- Xie, Y., Sha, Z., and Yu, M. 2008. Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology* 1(1): 9-23.
- Yagüe, J., and García, P. 2005. A remote sensing survey of vegetation communities adjacent to Myall Lakes, NSW, Australia. Global developments in environmental earth observation from space. Proceedings of the 25th EARSeL Symposium, Porto, Portugal.
- Zhang, L., and Baas, A. C. W. 2012. Mapping functional vegetation abundance in a coastal dune environment using a combination of LSMA and MLC: A case study of Kenfig NNR, Wales. *International Journal of Remote Sensing* 33(16): 5043-5071.
- Zhang, J. and Foody, G. M. 1998. A fuzzy classification of sub-urban land cover from remotely sensed imagery. *International Journal of Remote Sensing* 19(14): 2721-2738.

Appendix A: Field Data Collection

The following represents the types of field data collected during the summer of 2015. This sample is based on data collected at the Chantry Dunes (Southampton, Ontario, Canada) on July 3, 2015. The date, time, site number, and image reference were also recorded.

1) Location Information

- Location information was recorded using a hand-held GPS unit

2) Land-Cover Information

- The community level and community series based on the Ecological Land Classification for Southern Ontario was identified to facilitate image classification and analysis.

The Ecological Land Classification (ELC) Scheme Used in this Research Project.

Community Class	Community Series	Description
Beach / Bar	Open Beach / Sand	Exposed sands formed by current or historical shoreline or aeolian processes. Subjected to active shoreline processes; tree and shrub cover $\leq 25\%$
Water	Shallow Water	Water up to 2 metres in depth; emergent vegetation may be present but not dominant; no trees or shrub cover
Water	Open Water	Water > 2 metres in depth; no macrophyte vegetation, trees or shrub cover
Sand Dune	Treed Sand Dune	Relatively stable sand; $25\% \leq$ tree cover $\leq 60\%$
Sand Dune	Shrub Sand Dune	Sand is more stable, less disturbed; tree cover $\leq 25\%$, shrub cover $> 25\%$
Built-Up Area Impervious		Areas with buildings, pavement, and other anthropogenic features

(Sources: Ontario Ministry of Natural Resources, 2008; Lee et al., 1998)

3) Vegetation Cover

- Vegetation type was divided into native (N) or exotic (E)
- Coverage (expressed in %)
- Height was not measured given the sensitivity of the dune vegetation to disturbance.
- The quality and condition of the vegetation was based on a visual assessment and rated on the following scale:
- A= Excellent, B = Good, C = Satisfactory, and D = Poor


4) Weather Conditions

- Weather conditions were recorded to provide context to the photographs taken.

5) Photographic Record

- The photographic recording device was a digital camera
- The direction in which the photo was taken and a brief description of the scene was recorded to facilitate image classification and analysis.

The following table provides examples of the land-use/land-cover types used in this research project.

Land-Use/Land-Cover Type	Picture
Open Beach / Sand	 A wide, sandy beach with people and umbrellas. The beach is covered in light-colored sand. In the background, there are people sitting on towels or blankets, some with beach umbrellas. The ocean is visible in the distance under a cloudy sky.
Open Water	 A calm body of water with a distant shoreline. The water is a dark, muted greenish-brown color. In the distance, a low, dark shoreline is visible under a grey, overcast sky.

Treed Sand Dune



Shrub Sand Dune



Built-Up Area Impervious



Ground Truth Data Reporting Form			
Date: July 3, 2015		Time: 4:05 PM	
Recorder: Brodie			
Sampling ID Number: CH-01		Image Reference: 101-0161	
1. Location Information		2. Vegetation Condition	
* see location information below	Vegetation	N/A	Coverage? N/A
	Type?	N/A	
	Quality?	N/A	
	Condition?	N/A	
	Immediate threats from surrounding areas?	None	
3. Cover-Type Information			
Community Class:			
Community Series:		Built-Up Area Impervious	
Other Comments:		First observation of the day	
4. Weather Conditions			
Weather conditions:		Sunny, 22°C, slight breeze	Clouds (in 10ths)? 1
Other comments:		None	
5. Photographic Record			
<i>Direction</i>		<i>Description of Photo</i>	
(N NE E SE S SW W NW)			
W		Beach access point as seen from the parking lot on Front Street.	



101-0161

Ground Truth Data Reporting Form						
Date: July 3, 2015		Time: 3:22 PM		Recorder: Brodie		
Sampling ID Number: CH-02		Image Reference: 101-0058				
1. Location Information		2. Vegetation Condition				
* see location information below		Vegetation	N	Coverage?	80-90%	
		Type?	E			
		Quality?	A	B	C	D
		Condition?	A	B	C	D
		Immediate threats from surrounding areas?	Beach Access			
3. Cover-Type Information						
Community Class:		Sand Dune				
Community Series:		Shrub Sand / Treed Sand Dune				
Other Comments:		Photos were taken from the "bridge" over the small stream.				
4. Weather Conditions						
Weather conditions:		Sunny, 22°C, slight breeze		Clouds (in 10ths)? 1		
Other comments:						
5. Photographic Record						
<i>Photo #</i>	<i>Direction</i> (N NE E SE S SW W NW)		<i>Description of Photo</i>			
0058	SW		View of the small stream with Lake Huron in the distance			
0060	SE		Dune vegetation and sand dunes. Houses on the left are on Harmer Street. Note the height of the dune formations on the right			
0061	SW		View of the small stream with Lake Huron in the distance			
0064	NE		Dune vegetation and small trees			
0065	NE		Dune vegetation and small trees. Note the larger trees in the distance and on the right			






Image	Image Reference #
	<p data-bbox="1117 499 1237 541">101-0058</p>
	<p data-bbox="1117 1020 1237 1062">101-0060</p>
	<p data-bbox="1117 1562 1237 1604">101-0061</p>



Image	Image Reference #
	<p data-bbox="1114 569 1235 604">101-0064</p>
	<p data-bbox="1114 1094 1235 1129">101-0065</p>

Ground Truth Data Reporting Form							
Date: July 3, 2015		Time: 3:27 PM		Recorder: Brodie			
Sampling ID Number: CH-03		Image Reference: 101-0081					
1. Location Information			2. Vegetation Condition				
* see location information below			Vegetation	N	Coverage?	30 %	
			Type?	E			
			Quality?	A	B	C	D
			Condition?	A	B	C	D
			Immediate threats from surrounding areas?	Beach			
3. Cover-Type Information							
Community Class:		Sand Dune					
Community Series:		Shrub Sand Dune					
Other Comments:		This particular area of the beach did not have dune grass in 2012					
4. Weather Conditions							
Weather conditions:		Sunny, 22°C, slight breeze		Clouds (in 10ths)?	1		
Other comments:		First observation of the day					
5. Photographic Record							
<i>Direction</i>			<i>Description of Photo</i>				
(N NE E SE S SW W NW)							
NW			View of the beach with Chantry Island in the background				



101-0081

Ground Truth Data Reporting Form						
Date: July 3, 2015		Time: 3:33 PM		Recorder: Brodie		
Sampling ID Number: CH-04		Image Reference: 101-0083				
1. Location Information		2. Vegetation Condition				
* see location information below		Vegetation	N	Coverage?	90%	
		Type?	E			
		Quality?	A	B	C	D
		Condition?	A	B	C	D
		Immediate threats from surrounding areas?				
3. Cover-Type Information						
Community Class:		Sand Dune				
Community Series:		Shrub Sand Dune				
Other Comments:						
4. Weather Conditions						
Weather conditions:		Sunny, 22°C, slight breeze		Clouds (in 10ths)?	1	
Other comments:		None				
5. Photographic Record						
Photo #	Direction	Description of Photo				
	(N NE E SE S SW W NW)					
0083	SE	Portion of the Chantry Dune system as viewed from the Nature Trail; the houses in the background are on Harmer Street				
0086	W	View west from the Nature Trail pathway in the Chantry Dune system.				

Image	Image Reference
	<p data-bbox="1112 569 1235 604">101-0083</p>
	<p data-bbox="1112 1094 1235 1129">101-0086</p>

Ground Truth Data Reporting Form			
Date: July 3, 2015		Time: 3:36 PM	
Recorder: Brodie			
Sampling ID Number: CH-05		Image Reference: 101-0088	
1. Location Information		2. Vegetation Condition	
* see location information below		Vegetation	N/A Coverage? N/A
		Type?	N/A
		Quality?	N/A
		Condition?	N/A
		Immediate threats from surrounding areas?	Beach Access
3. Cover-Type Information			
Community Class: Sand Dune			
Community Series: Shrub Sand Dune			
Other Comments:			
4. Weather Conditions			
Weather conditions: Sunny, 22°C, slight breeze		Clouds (in 10ths)?	1
Other comments: First observation of the day			
5. Photographic Record			
<i>Direction</i>		<i>Description of Photo</i>	
(N NE E SE S SW W NW)			
SW		Entrance to two of the main pathways through the Chantry Dune system: "Beach Access" and the "Nature Trail"	



101-0088

Ground Truth Data Reporting Form							
Date: July 3, 2015		Time: 3:41 PM		Recorder: Brodie			
Sampling ID Number: CH-06		Image Reference: 101-0097-98					
1. Location Information			2. Vegetation Condition				
* see location information below			Vegetation	N	Coverage?	95 - 100%	
			Type?	E			
			Quality?	A	B	C	D
			Condition?	A	B	C	D
			Immediate threats from surrounding areas?	Beach Access			
3. Cover-Type Information							
Community Class:		Sand Dune					
Community Series:		Shrub Sand Dune					
Other Comments:							
4. Weather Conditions							
Weather conditions:		Sunny, 22°C, slight breeze		Clouds (in 10ths)?	1		
Other comments:		None					
5. Photographic Record							
Photo #	Direction	Description of Photo					
	(N NE E SE S SW W NW)						
0097	NW	Lake Huron and part of the main beach (in the distance) as seen through one of the pathways through the dune system					
0098	SW	Large section of dune grass					

Image	Image Reference
	101-0097
	101-0098

Ground Truth Data Reporting Form							
Date: July 3, 2015		Time: 3:49 PM		Recorder: Brodie			
Sampling ID Number: CH-07		Image Reference: 101-0118					
1. Location Information			2. Vegetation Condition				
* see location information below			Vegetation	N	Coverage?	95%	
			Type?	E			
			Quality?	A	B	C	D
			Condition?	A	B	C	D
			Immediate threats from surrounding areas?	Beach Access			
3. Cover-Type Information							
Community Class:		Sand Dune					
Community Series:		Shrub Sand Dune					
Other Comments:							
4. Weather Conditions							
Weather conditions:		Sunny, 22°C, slight breeze		Clouds (in 10ths)?	1		
Other comments:		First observation of the day					
5. Photographic Record							
<i>Direction</i>			<i>Description of Photo</i>				
(N NE E SE S SW W NW)							
NW			Dune vegetation (grasses, forbs, shrubs, small trees) and Chantry Island in the distance.				



101-0118

Ground Truth Data Reporting Form						
Date: July 3, 2015		Time: 3:51 PM		Recorder: Brodie		
Sampling ID Number: CH-08		Image Reference: 101-0124				
1. Location Information		2. Vegetation Condition				
* see location information below		Vegetation	N	Coverage?	100%	
		Type?	E			
		Quality?	A	B	C	D
		Condition?	A	B	C	D
		Immediate threats from surrounding areas?	Beach Access			
3. Cover-Type Information						
Community Class:	Sand Dune					
Community Series:	Shrub Sand Dune					
Other Comments:	This section of dune grass has grown lake-ward significantly, impeding access to the main beach. As a child, this dune grass was not present and area was part of the main beach.					
4. Weather Conditions						
Weather conditions:	Sunny, 22°C, slight breeze			Clouds (in 10ths)?	1	
Other comments:	None					
5. Photographic Record						
<i>Direction</i>			<i>Description of Photo</i>			
(N NE E SE S SW W NW)						
S			Large section of dune grass with main beach in distance			



Ground Truth Data Reporting Form				
Date: July 3, 2015		Time: 3:58 PM		Recorder: Brodie
Sampling ID Number: CH-09		Image Reference: 101-0145		
1. Location Information		2. Vegetation Condition		
* see location information below	Vegetation	N	Coverage?	70%
	Type?	E		
	Quality?	A	B	C D
	Condition?	A	B	C D
	Immediate threats from surrounding areas?	Beach		
3. Cover-Type Information				
Community Class:	Beach / Bar			
Community Series:	Open Beach			
Other Comments:	Beach area is noticeably smaller than previous years			
4. Weather Conditions				
Weather conditions:	Sunny, 22°C, slight breeze		Clouds (in 10ths)?	1
Other comments:	None			
5. Photographic Record				
<i>Photo #</i>	<i>Direction</i> (N NE E SE S SW W NW)	<i>Description of Photo</i>		
0145	E	Section of dune grass amongst the wooden lookout platform		
0149	NW	Beachgoers enjoying the beautiful July day with Chantry Island in the distance.		

Image	Image Reference
	<p data-bbox="1114 569 1235 604">101-0145</p>
	<p data-bbox="1114 1094 1235 1129">101-0149</p>



Appendix B: GeoEye-1 Data - Descriptive Statistics and Histograms

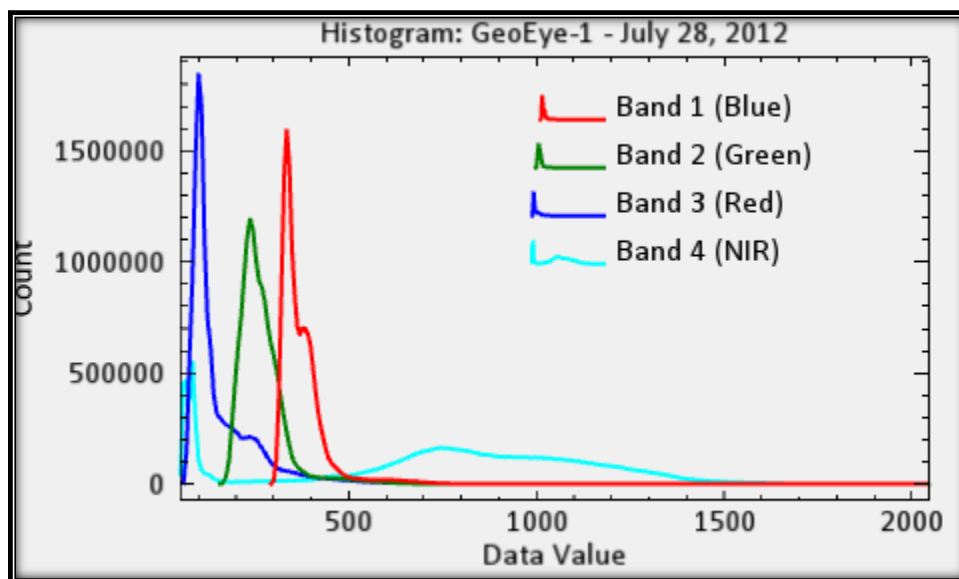
This appendix includes the descriptive statistics and histograms (band-by-band) for both the GeoEye-1 remote sensing image that was used in this research project. All image preprocessing operations and subsequent analyses were performed using ENVI 5.2.

GeoEye-1: July 28, 2012

Table B1: Descriptive Statistics for Bands 1-4 of GeoEye-1 data (acquired July 28, 2012)

Band Number	Minimum	Maximum	Mean*	Standard Deviation*
1 (Blue)	293	2047	377.8	68.4
2 (Green)	157	2047	272.4	68.1
3 (Red)	60	2047	161.1	97.3
4 (NIR)	52	2047	755.8	389.1

*NOTE: These values have been rounded to the nearest tenth.



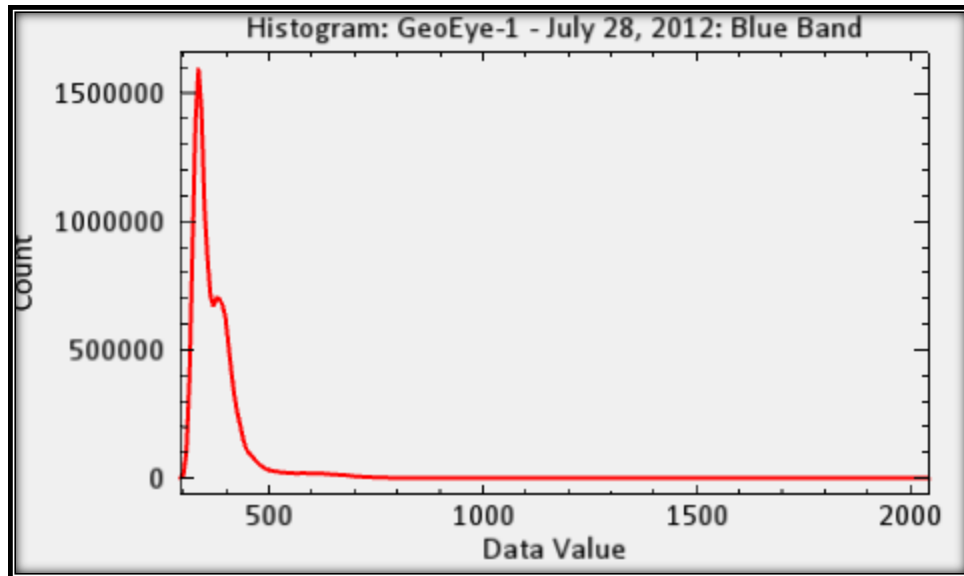


Figure B.1: Histogram of band 1 (Blue) of GeoEye-1 data acquired over Southampton, Ontario, on July 28, 2012.

	Comments
Shape	The histogram appears to be unimodal
Main Characteristics	The majority of image pixels have lower digital numbers or DN's (low reflectance) with a peak at ~ 350; this would be expected for this area (lots of water = low reflectance; lots of vegetation = low reflectance)
Normal Distribution?	No (strong right skew)
Anomalies?	No obvious data anomalies
Cause/Explanation	N/A

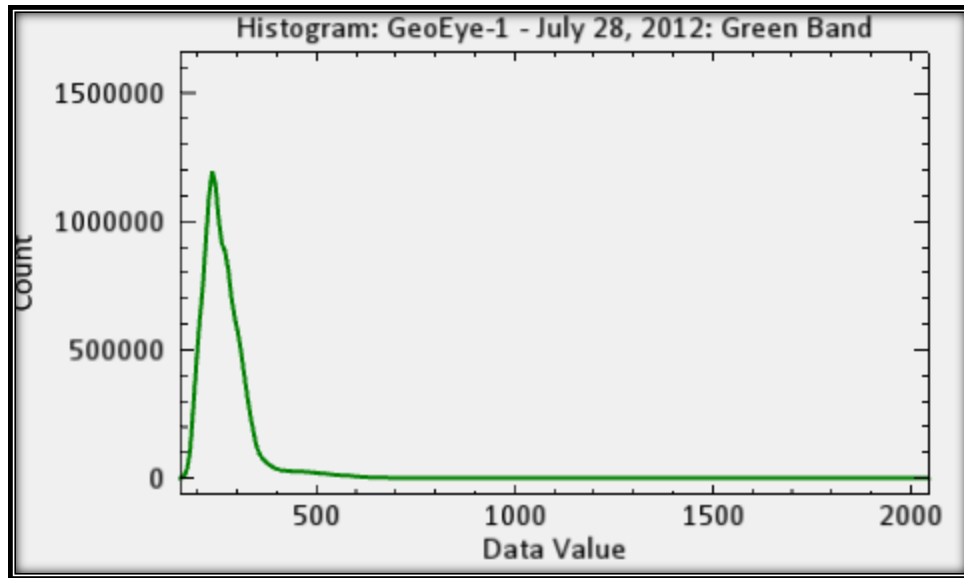


Figure B.2: Histogram of band 2 (Green) of GeoEye-1 data acquired over Southampton, Ontario, on July 28, 2012.

	Comments
Shape	The histogram appears to be unimodal
Main Characteristics	The majority of image pixels have lower DN's (low reflectance) with a peak at ~ 250; this would be expected given the amount of vegetation in the area (healthy vegetation reflects visible green energy).
Normal Distribution?	No (strong right skew)
Anomalies?	No obvious data anomalies
Cause/Explanation	N/A

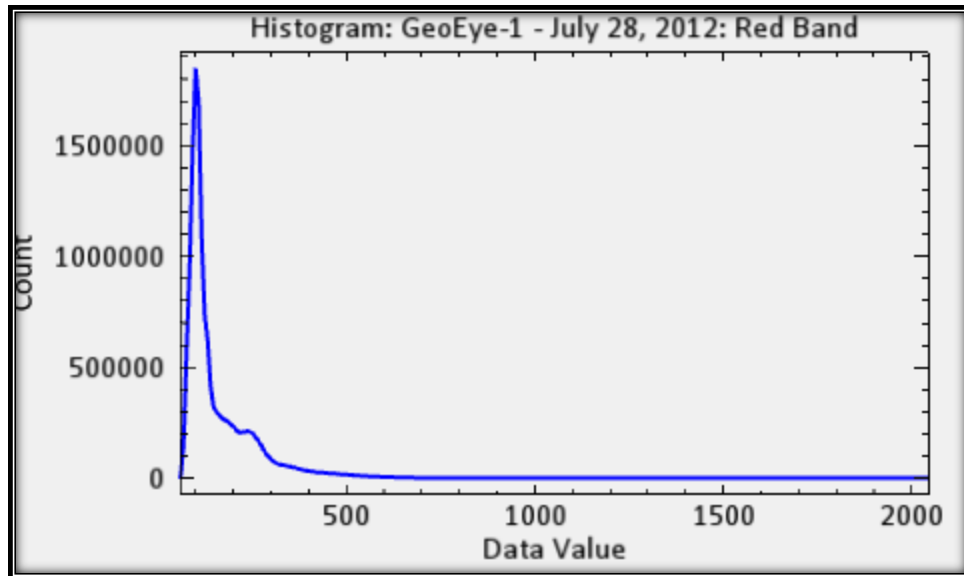


Figure B.3: Histogram of band 3 (Red) of GeoEye-1 data acquired over Southampton, Ontario, on July 28, 2012.

	Comments
Shape	The histogram appears to be unimodal
Main Characteristics	The majority of image pixels have lower DN's (low reflectance) with a peak at ~100; this would be expected given the amount of vegetation present in the image. (Red is the absorption band of healthy green vegetation.)
Normal Distribution?	No (strong right skew)
Anomalies?	No obvious anomalies here
Cause/Explanation	N/A

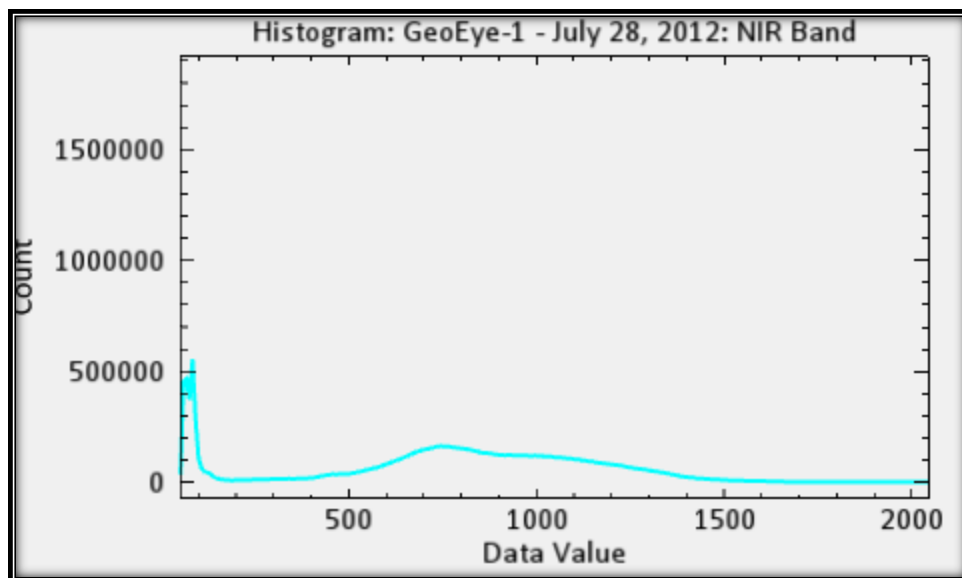


Figure B.4: Histogram of band 4 (NIR) of GeoEye-1 data acquired over Southampton, Ontario, on July 28, 2012.

	Comments
Shape	The histogram appears to be unimodal
Main Characteristics	The majority of image pixels have lower DN's (low reflectance) with a peak at ~100; this would be expected for this area (lots of water = low reflectance; lots of veg = high reflectance)
Normal Distribution?	No (strong right skew)
Anomalies?	No obvious data anomalies here. The two modal classes represent water and vegetation.
Cause/Explanation	N/A

Additional Comments:

- The values obtained above make sense based on the image components that comprise this image scene.
 - The image contains a lot of vegetation and water; this explains the low mean and standard deviation for the blue band (band 1) and the high NIR mean.
 - Given the types of vegetation present (e.g., mixed forest, agricultural crops) combined with the time of year (late July), the high NIR mean and standard deviation (STD) make sense. In addition, this also explains the lower mean for the red band (band 3).
 - The large number of water pixels, in addition to rural towns, explains the higher NIR STD. There are many different land-use/land-cover types in this image that would strongly influence this value.
 - The maximum values of 2047 are a bit more suspicious as remote-sensing datasets do not normally reach the highest possible digital number in all four bands.
-

Appendix C: QuickBird - Descriptive Statistics and Histograms

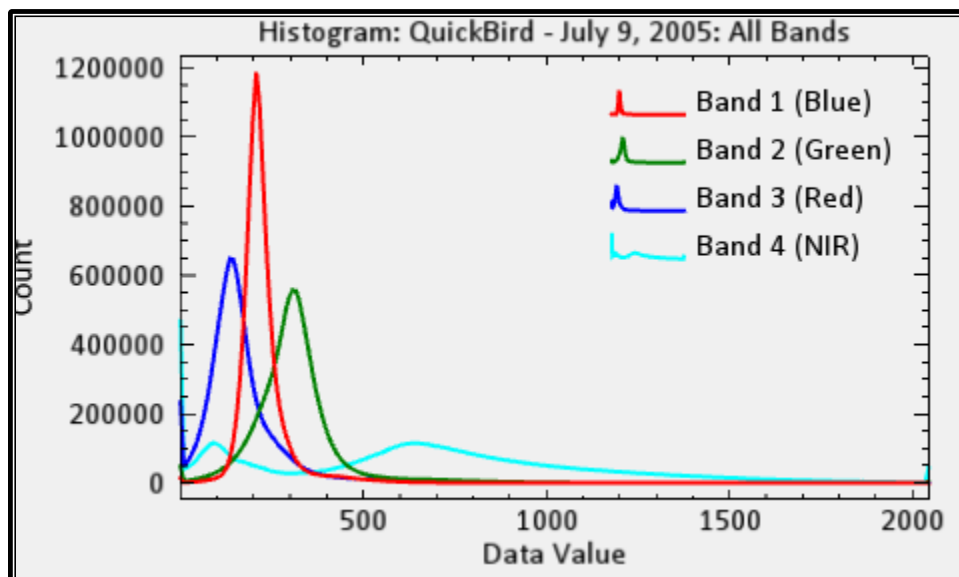
This appendix includes the descriptive statistics and histograms (band-by-band) for the QuickBird remote sensing image that was used in this research project. All image preprocessing operations and subsequent analyses were performed using ENVI 5.2.

QuickBird: July 9, 2005

Table C1: Descriptive Statistics for Bands 1-4 of QuickBird data (acquired July 9, 2005)

Band Number	Minimum	Maximum	Mean*	Standard Deviation*
1 (Blue)	1	2047	229.9	75.7
2 (Green)	1	2047	320.8	135.8
3 (Red)	1	2047	176.2	125.0
4 (NIR)	1	2047	671.4	441.0

*NOTE: These values have been rounded to the nearest tenth.



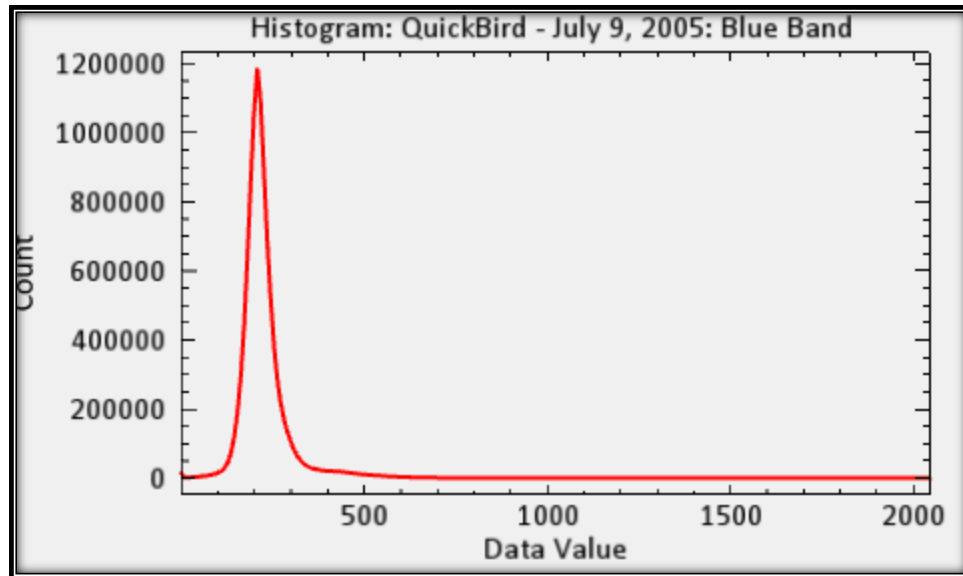


Figure C.1: Histogram of band 1 (Blue) of QuickBird data acquired over Southampton, Ontario, on July 9, 2005.

	Comments
Shape	The histogram appears to be unimodal
Main Characteristics	The majority of image pixels have lower DN's (low reflectance) with a peak at ~ 200; this would be expected for this area (lots of water = low reflectance; lots of vegetation = low reflectance)
Normal Distribution?	No (strong right skew)
Anomalies?	No obvious data anomalies
Cause/Explanation	N/A

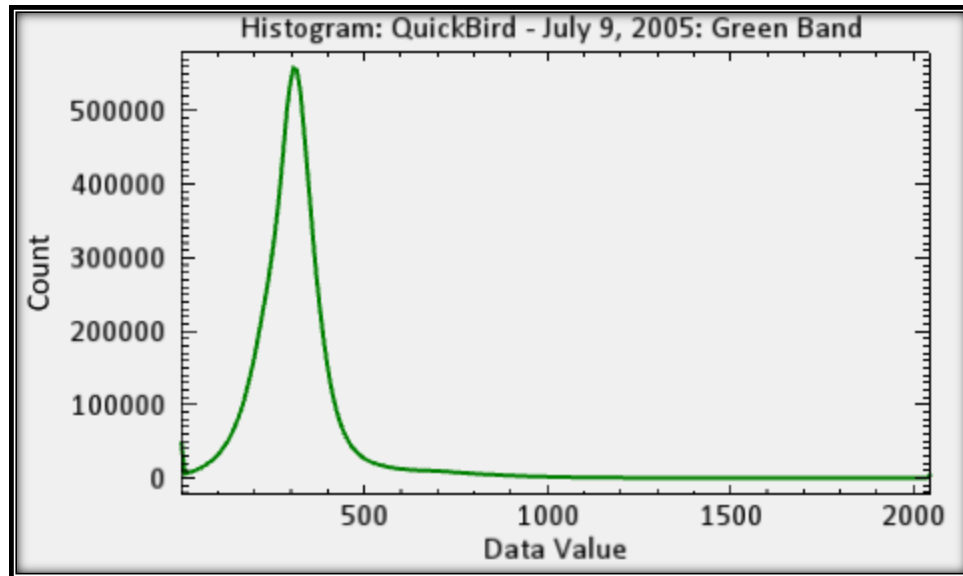


Figure C.2: Histogram of band 2 (Green) of QuickBird data acquired over Southampton, Ontario, on July 9, 2005.

	Comments
Shape	The histogram appears to be unimodal
Main Characteristics	The majority of image pixels have lower DN's (low reflectance) with a peak at ~ 300; this would be expected given the amount of vegetation in the area (healthy vegetation reflects visible green energy).
Normal Distribution?	No (strong right skew)
Anomalies?	No obvious data anomalies
Cause/Explanation	N/A

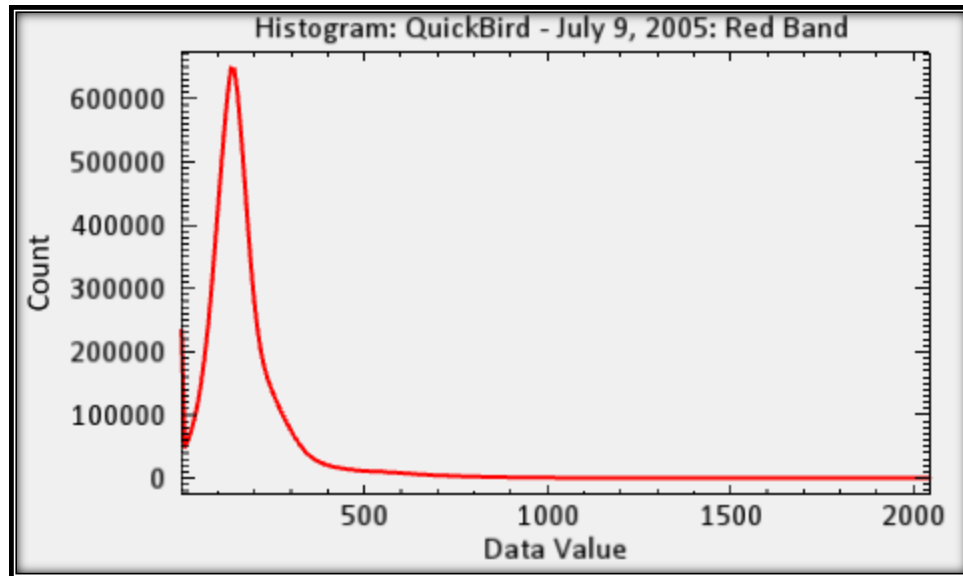


Figure C.3: Histogram of band 3 (Red) of QuickBird data acquired over Southampton, Ontario, on July 9, 2005.

	Comments
Shape	The histogram appears to be unimodal
Main Characteristics	The majority of image pixels have lower DN's (low reflectance) with a peak at ~ 150; this would be expected given the amount of vegetation present in the image. (Red is the absorption band of healthy green vegetation.)
Normal Distribution?	No (strong right skew)
Anomalies?	No obvious anomalies
Cause/Explanation	N/A

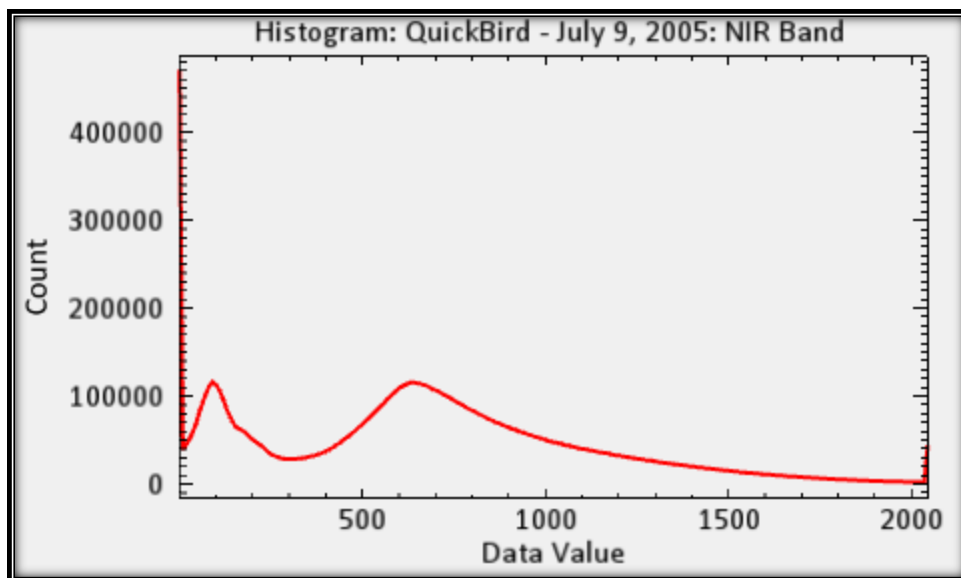


Figure C.4: Histogram of band 4 (NIR) of QuickBird data acquired over Southampton, Ontario, on July 9, 2005.

	Comments
Shape	The histogram appears to be bimodal
Main Characteristics	The majority of image pixels have lower DN's with peaks at ~ 100 and ~ 650; this would be expected for this area (lots of water = low reflectance; lots of veg = high reflectance)
Normal Distribution?	No (strong right skew)
Anomalies?	No obvious anomalies
Cause/Explanation	N/A

Additional Comments

- The values obtained above make sense based on the image components that comprise this image scene.
 - The image contains a lot of vegetation and water; this explains the low mean and standard deviation for the blue band (band 1) and the high NIR mean.
 - Given the types of vegetation present (e.g., mixed forest, agricultural crops) combined with the time of year (late July), the high NIR mean and standard deviation make sense. In addition, this also explains the lower mean for the red band (band 3).
 - The large number of water pixels, in addition to rural towns, explains the higher NIR STD. There are many different land-use/land-cover types in this image that would strongly influence this value.
 - The maximum values of 2047 are a bit more suspicious as remote-sensing datasets do not normally reach the highest possible digital number in all four bands.
 - The minimum values of 1 are also suspicious as remote-sensing datasets do not normally reach the lowest possible digital number in all four bands.
-

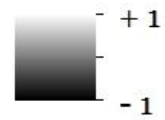
Appendix D

Normalized Difference Vegetation Index Map of the Chantry Dune System

July 2005



NDVI Index
Value



0 25 50 100 Metres
|-----|

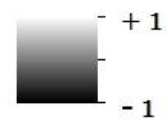
Appendix E

Normalized Difference Vegetation Index Map of the Chantry Dune System

July 2012



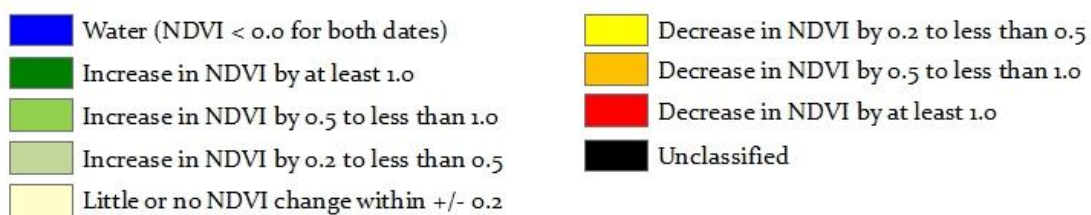
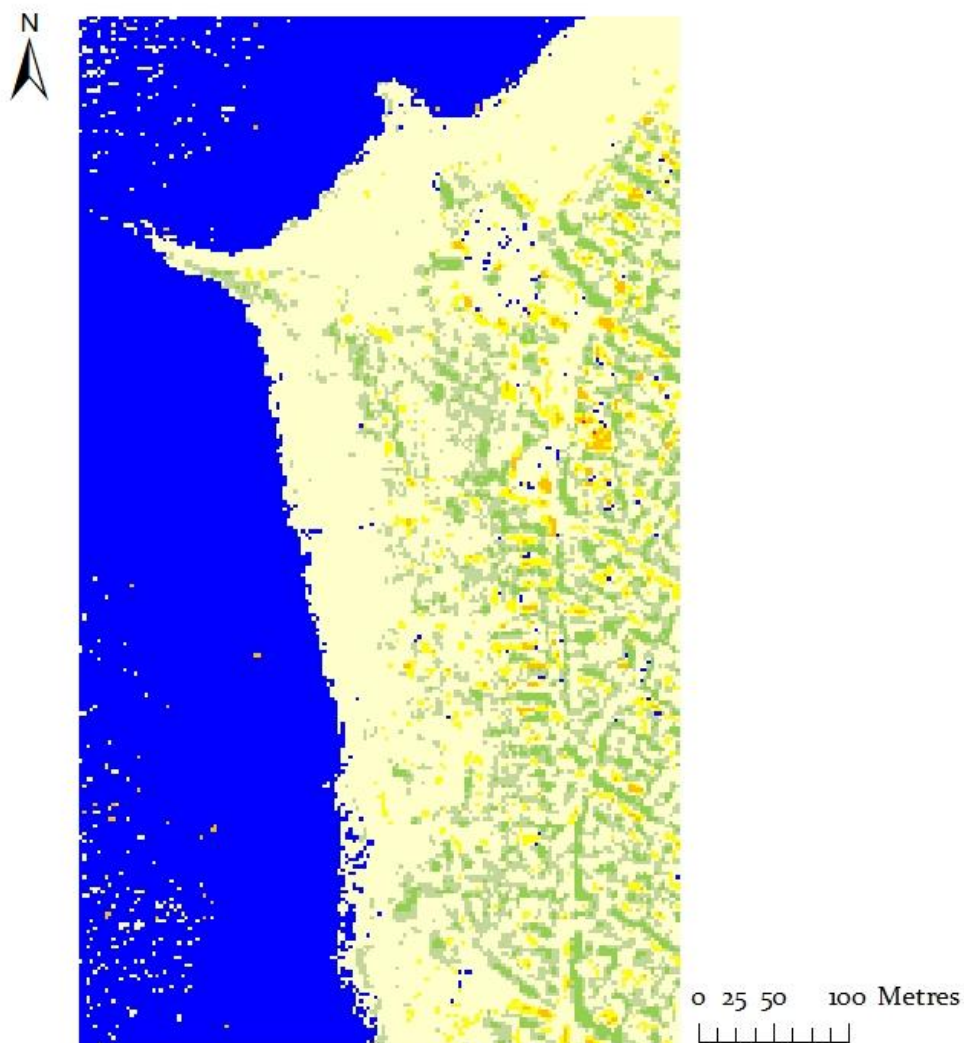
NDVI Index
Value



0 25 50 100 Metres
| | | | |

Appendix F

Post-Classification Change Comparison of NDVI Clusters: Chantry Dune System - Southampton, Ontario July 2005 - July 2012



Appendix G

Land-Use/Land-Cover Classification of the Chantry Dune System: Southampton, Ontario



0 30 60 120 Metres
|-----|-----|-----|-----|

Legend

Built-Up Area Impervious	Open Water	Treed Sand Dune
Open Beach	Shrub Sand Dune	Shallow/Turbid Water

Source: GeoEye-1 (2 m); Acquired: July 28, 2012; MLC Algorithm; Bands 1-4